Capturing the Complexity and Dynamics of Positive Human Health: Conceptual and Methodological Considerations

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Abstract and Keywords

This chapter illustrates how recent advances in longitudinal methodology can be applied to diverse issues of interest to positive psychologists. The rules for doing research that can net the highest stakes in understanding are, to a considerable extent, the rules of design and measurement. The aim of the chapter is to describe how contemporary theories of well-being may be empirically evaluated using a variety of research designs and analytical techniques that can fully capture the complexity and dynamics of positive human health. Throughout, the chapter identifies unresolved methodological challenges associated with the measurement and analysis of between- and within-person phenomena and elaborates on the implications of these challenges for process research in positive psychology.

Keywords: longitudinal methodology, dynamic systems, intensive measurement designs, multilevel SEM, idiographic evidence, nomothetic evidence

> The life, the fortune and the happiness of every one of us depend on our knowing something about the rules of a game infinitely more difficult than chess. The chessboard is the universe, the pieces are the phenomena of the universe. The player on the other side is hidden from us. We know that his play is always fair, just and patient. But we also know, to our cost, that he never overlooks a mistake, or makes the smallest allowance for ignorance. To the man who plays well, the highest stakes are paid, with the sort of flowering generosity with which the strong show delight in strength. And he who plays ill is check-mated—without haste and without remorse. What I mean by education is learning the rules of this mighty game.
>
> —Thomas H. Huxley (1948), *A Liberal Education*

The rules for doing research that can net the highest stakes in understanding are, to a considerable extent, the rules of design and measurement. Many forms of data analysis can lead to the same conclusion when a study is well designed, but even the most intricate and powerful data analysis methods cannot extract a dependable basis for understanding when a study is poorly designed. Design is critical. At the core of good design is good measurement. If the variables of an otherwise adequate design are not measured well, if they are not reliable and reliably independent, the results from analysis, however intricate and powerful these may be, can be of little value and may be quite misleading. It is therefore (p. 142) important to know the design properties of measurements, for these properties indicate what the results from analyses can and cannot reveal.

In this chapter, we illustrate how recent advances in longitudinal methodology can be applied to diverse issues of interest to positive psychologists. Although we do not intend to provide an in-depth review, we do strive to critically evaluate and address conceptual and methodological issues surrounding the need for (a) reliable and theory-driven measures of positive health and well-being, (b) study designs that link information at different levels of analysis, and (c) innovative methodological approaches that are sensitive to complex dynamic relationships. Progress on these issues requires a greater understanding of process. The aim of this chapter is to help build such understanding by describing how contemporary theories of well-being (i.e., subjective well-being and psychological well-being) may be empirically evaluated using innovative research designs (e.g., intensive repeated-measurement "burst" designs) and analytical techniques (e.g., multilevel structural equation models, location scale models, and dynamic systems analysis) that can fully capture the complexity and dynamics of positive human health. We conclude with a brief discussion of methodological issues that might profitably be considered in future research.

Elaborating the *Positive* in Positive Psychology

Any theory that purports to be scientific should account for the extant evidence—ideally, all of the evidence. It should also give indications of where new evidence should be sought that can test the theory and lead to modifications. A clear and detailed theoretical model, thus, is a necessary foundation for all empirical research. In an everyday sense of things, positive psychology is a theory of strengths and potentials in which there are individual differences within the human species. Among the strengths and potentials that characterize humans in contrast to other species are some that allow the description of one individual as different from another. In all languages of the world, there are words used to describe positive aspects of human functioning in which people differ. These positive aspects of human health have been referred to with the term *well-being*. Positive psychology is thus a theory of human well-being.

There is a problem in describing theory in this way, however. "Well-being" is a singular word. But the accumulated evidence indicates that there is more than one kind of quality that is said to be characteristic of human well-being. These qualities appear to be positively correlated, but no unifying principle (such as the principle that unites different forms of energy—kinetic, heat, chemical, etc.) has been established that unites different forms of well-being. Thus, the problem is that use of the singular word *well-being* fosters the belief that different positive human experiences are all forms of one thing, well-being, when the empirical evidence points to many more (e.g., Ryff, 1989). It is possible that there is one organizing principle pervading all human well-being. It is reasonable that there should be. It would be valuable to have a measure of it. But the evidence adduced thus far does not indicate that principle. Studies that can lead to such a discovery, therefore, need to be based on good understanding of measurement evidence.

Measuring Dimensions of Positive Health and Well-Being

The theories of subjective well-being (Diener, 1984) and psychological well-being (Ryff, 1989) were developed in response to simple structure evidence of covariation among measures of human well-being. The theories are largely descriptive, an account of what the dimensions are that characterize the human capacity for generating and coping with complexities. But the theories are also a description of variables with which measures of human well-being correlate, an account of how and why such relationships come about. The theories are thus also explanatory. Although both theories aim to describe how people evaluate their lives, each emphasizes different aspects of this evaluation.

Subjective well-being (SWB) defines evaluations in terms of three elements: reports of positive and negative affect, and judgments of overall life satisfaction (Diener, 1994). A key assertion of this model is that positive emotion defines a dimension of well-being that cannot be accounted for through the assessment of subjective distress, depressed affects, or other negative emotions (Watson, Clark, & Tellegen, 1988). Overall SWB, then, is thought to depend on the promotion of positive states, the diminution of negative states, and the cognitive structures that support judgments that weigh the positive in life more heavily than the negative.

In contrast, psychological well-being (PWB) parses well-being into six elements: judgments of self-acceptance, personal growth, purpose in life, positive relations with others, environmental mastery, and autonomy (Keyes, 2009; Ryff & Keyes, 1995). The authors of this approach distinguish their (p. 143) model as one that focuses on stable, "stick-to-the-ribs" qualities of the person in comparison to models of happiness that rely on subjective reports of positive states that are more transitory. Indeed, measures of the positive differ dramatically in the proportion of variance in their scores that constitute a stable trait (see Kenny & Zautra, 2001), versus a state, which varies within a person over time. Seen in this light, the two approaches, SWB and PWB, may be thought of as more complementary, tackling different temporal aspects of the assessment of well-being.

Progress has been made in identifying and measuring the separate elements of SWB and PWB. Reliable measures of these elements have been developed—the Positive and Negative Affect Schedule (PANAS; Watson et al., 1988), the Satisfaction With Life Scale (SWLS; Diener, Emmons, Larsen, & Griffin, 1985), and the Psychological Well-Being Scales (Ryff, 1989). Different forms of evidence have been put forth to indicate the validity of these elements. Evidence of discriminant validity of SWB elements has been supported with multi-trait, multi-method analyses (Lucas, Diener, & Suh, 1996). Evidence of convergent validity of PWB elements has been indicated with common factor analyses (Ryff & Keyes, 1995). And evidence for the convergent and discriminant validity of all nine SWB and PWB elements has been supported with confirmatory factor analyses (Keyes, Shmotkin, & Ryff, 2002). Thus, it has become clear that the phenomenon referred to as *well-being* is a mosaic of many component parts. This mosaic can be partitioned into a parsimonious set of dimensions, representing measurements that account for individual differences among a large number of these components.

The Need for Idiographic Evidence

Although the foundational evidence has provided a basis for understanding the phenomenon of well-being, other basic information is needed to establish the nature of the phenomenon. That is, individuals are believed to exhibit coherent patterns of experience that cannot be fully described or explained merely by locating those individuals within a fixed system of trait dimensions (Allport, 1966). Thus, although *nomothetic* (between-person) analyses have yielded converging evidence for the construct validity of measures of SWB and PWB, very little attention has been given to investigating *idiographic* (within-person) relations among these elements (Ong, Horn, & Walsh, 2006).

Perhaps nowhere more than in positive psychology is the importance of repeated measurement and analysis so essential (Ong & van Dulmen, 2006). Studies that include only one occasion of measurement provide a good example of ambiguities that arise when an assumption of stability is made. These ambiguities have been described in detail by Nesselroade (1991). When participants are measured on only one occasion, the *inter-individual* variability in the measurements can reflect three different sources: (1) stable differences among people (traits), (2) *intra-individual* variability (states), and (3) temporal measurement error. These three possible sources of variation are inextricably confounded when data are obtained on only one occasion, and it is impossible to separate them (Nesselroade, 1991b).

Because phenomena also may vary reliably and lawfully within individuals, conclusions based on nomothetic research are premature without idiographic information (Nesselroade, 1991b). With few exceptions (e.g., Merz & Roesch, 2011; Rush & Hofer, 2014; Wessman & Ricks, 1966; Zevon & Tellegen, 1982); however, construct validation of SWB and PWB measures has been based largely on nomothetic, rather than idiographic, data. Little is known about whether the separate elements of SWB and PWB can be reliably and independently observed within individuals studied across time. To our knowledge, no study has provided evidence indicating that the reliability and independence of measurements that have been indicated in between-person analyses of both SWB and PWB (e.g., Keyes et al., 2002) also obtains for within-person observations of these phenomena. Evidence of this possibility is needed if SWB and PWB theories are to move beyond being simple descriptive empirical generalizations of research findings to provide some indications of how positive health and well-being is organized across individuals, how such experience develops across the lifespan, or how individual differences in well-being come about.

The Need for Evidence of Measurement Invariance

Implicit in the comparison of groups and individuals is the assumption of equivalence of measurement. This assumption, however, is rarely tested directly in research in positive psychology. Yet the interpretation of either *interindividual* or *intraindividual* results, based on non-equivalent measurements, is riddled with ambiguity (Horn & McArdle, 1992). Evidence of measurement invariance is fundamentally important for evaluating both nomothetic and idiographic evidence. For, in each case, before any construct validation results can be (p. 144) sensibly interpreted, there must be assurances that the scales measure the same attributes in the same way in different groups and circumstances. If scales do not measure the same factors (a) in the same way in different groupings of people or (b) in the same people measured in different places and times, there is no logical basis for interpreting the results of analyses of differences between means or variances or correlations (Meredith & Horn, 2001).

Do people interpret the items of SWB and PWB scales in comparable ways? A consistent finding in the literature is that women score slightly lower than men on measures of SWB (Lucas & Gohm, 2000), but significantly higher than men on PWB measures of “positive relations with others” and “personal growth” (Ryff & Keyes, 1995). Although these observed differences may reflect valid psychological differences between men and women, it is also possible that the item content of certain SWB and PWB measures may differentially capture aspects of well-being that women are more likely to endorse, whereas the item content of other measures may summarize aspects of well-being that men are more likely to endorse (Ong et al., 2006). Establishing that an instrument is factorially invariant, therefore, provides evidence not only that respondents from different groups can be legitimately compared on the same scale, but also that observed group-mean differences in raw scores reflect valid and meaningful group differences at the level of the latent variable assumed to underlie those scores. Evidence of measurement invariance across time, therefore, is a necessary prerequisite for understanding all other evidence pertaining to the temporal validity of such constructs (Horn & McArdle, 1992; Meredith & Horn, 2001).

Designing Studies of Change

Because the process of change represents a main, central issue for the study of positive psychology, research designs are needed that can capture ongoing processes of growth and adaptation. Cross-sectional (i.e., single-occasion) designs fail to account for the potential variability around trait levels. When measures vary both within-person across time as well as between people, measuring only once forces all systematic within-person variations to be grouped together and treated as random measurement error. As a result, the cross-sectional measure carries both between-person information (i.e., characteristic individual level) and within-person information (i.e., deviations from individual level) with no possibility of disentangling the two sources of variation with only a single measurement (Curran & Bauer, 2011; Hoffman & Stawski, 2009). Assuming that a construct is stable can be problematic when the construct does indeed systematically vary over time, and it can lead to conclusions about individual differences that are confounded with within-person variance (e.g., Rush & Hofer, 2014). In this section, we highlight the utility of intensive repeated-measurement burst designs. Arguments are presented that bear on the value of these designs as underutilized approaches that appear particularly appropriate to the investigation of intraindividual change and variability in SWB and PWB. Throughout, we argue that the strength of the process approach is an essential shift away from cross-sectional, single-variable explanations, and toward person-centered accounts of positive health.

Intensive Burst Designs

Many of the most interesting research questions addressed in positive psychology relate to how individuals change over time and what factors influence the development of adaptive change. Longitudinal designs are particularly well suited for evaluating models of *long-term* change or development. However, there are times when the investigator is interested in closely observing change while it is occurring. Intensive measurement designs consist of frequent, closely spaced assessments (e.g., daily diary, ecological momentary assessment) that enable within-person variations to be disaggregated from between-person differences. In comparison with traditional longitudinal panel designs, intensive burst designs allow researchers to observe processes of *short-term* change within a rapidly changing window of time. Furthermore, incorporating several measurement bursts that are repeated at more widely spaced intervals (e.g., one year) enables change to be measured on multiple time scales to allow short-term fluctuations to be disaggregated from long-term changes.

The growing availability of electronic diaries and mobile assessment tools (e.g., smartphones, tablets) allows the study of the determinants and consequences of changes in well-being within people's everyday lives. The short time intervals between events and self-reports improves accuracy and reduces bias. In addition to these improvements in measurement precision, repeated assessments of the same person over time solve a serious problem in inference that plagues research in this area. Variables that predict differences between people on an outcome like happiness may have no (p. 145) effect or even the opposite effect on the same outcome when measured as a change within the person observed over time (Tennen & Affleck, 1996). Only careful studies that evaluate changes over time in both the independent and dependent variables can safely make such assertions. Finally, electronic diaries have methodological advantages that are connected to the use of intensive burst designs. First, electronic diaries allow individuals to report their behavior and experiences over the range of situational circumstances experienced in everyday life. Second, they allow the statistical modeling of behavior over time. Third and most important, such procedures can test, rather than assume, the validity of the nomothetic approach.

Methodologies That Are Sensitive to Dynamic Relationships

In addition to designing studies of change and variation, one critical aspect of testing theories of change is fitting models of change to empirical data. In this section, we describe analytical possibilities that are available for intensive burst designs. We focus our comments on multiple data-analysis strategies, namely those associated with multilevel structural equation modeling, location scale models, and dynamic systems analysis, respectively. For a more thorough discussion of other statistical approaches for modeling change, the interested reader is referred to Collins and Horn (1991), Collins and Sayer (2000), Kenny and Zautra (2001), McArdle and Hamagami (2001), Raudenbush (2001), and Curran and Bauer (2011).

Multilevel Structural Equation Models

Multilevel structural equation models (SEM) are a flexible system of models that enables the ideographic and nomothetic information to be modeled together. A key question in the measurement of SWB and PWB is whether the covariance structure that has been identified at the between-person level with cross-sectional designs is also present within individuals, measured repeatedly over time. That is, are the components of SWB and PWB structured the same way within an individual as they are across individuals? Multilevel factor analyses can be employed on intensive repeated-measurement data to simultaneously examine both a within-person and a between-person factor structure. In multilevel factor analysis, the within-person factor structure reflects common covariance in the indicators at each specific occasion, pooled across occasions and individuals. The between-person factor structure reflects common covariance in individual levels of indicators aggregated across time (i.e., person-mean level). Similar to conventional factor analysis, the adequacy of the model can be assessed with a variety of fit indices, which include both global fit indices (e.g., comparative fit index [CFI]; root mean square error of approximation [RMSEA]) and level-specific fit indices (e.g., standardized root mean square residual [SRMR] within/between). Additional level-specific model fit indices can also be computed (see Ryu & West, 2009).

Multilevel confirmatory factor analysis (CFA) allows the within-person variance to be disaggregated from the between-person variance, while still attenuating for measurement error at both levels. The multilevel measurement model can be expressed by the following equation (Muthén, 1991; Preacher, Zyphur, & Zhang, 2010):

$$Y_{ij} = v + \lambda_w \eta_{ij} + \varepsilon_{ij} + \lambda_b \eta_i + \varepsilon_i,$$

where Y_{ij} is a p-dimensional vector of observed variables for individual i on occasion j, where p is the number of observed indicators; v is a p-dimensional vector of intercepts; λ_w is a p X q within-person factor loadings matrix, where q is the number of latent variables; λ_b is a p X q between-person factor loadings matrix; η_{ij} and η_i are q-dimensional vectors of within-person and between-person latent variables, respectively; and ε_{ij} and ε_i are p-dimensional vectors of within-person and between-person specific factors (i.e., residuals), respectively. At the between-person level, the indicators are person-specific means of each within-person indicator that are aggregated in order to adjust for unreliability in sampling error (see Lüdtke et al., 2008, for further details), such that the between-person indicators are represented as latent means.

Figure 11.1 provides an example of a multilevel CFA for an adapted version of the Satisfaction with Life Scale (SWLS), measured daily for 14 consecutive days. In this case, a single factor at both the within- and between-person levels fit the data extremely well, with all five items loading onto this single factor. These five items reliably covaried within a person across occasions (i.e., on occasions when one item deviated from typical levels, the other four items also deviated in the same direction) and between people (i.e., individuals who were higher on one item relative to others were also higher on the other items). The within-person structure will not always match the between-person structure. For example, Rush and Hofer (2014) found that the PANAS was best represented by two (p. 146) inversely related factors (PA and NA) at the within-person level, but independent PA and NA factors at the between-person level.

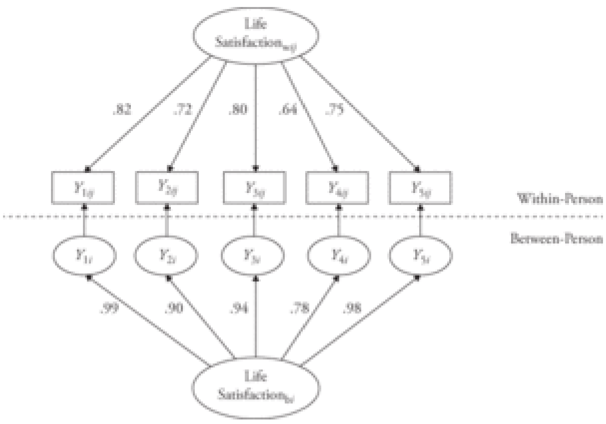

Figure 11.1 Multilevel confirmatory factor model of daily life satisfaction with one within-person factor and one between-person factor. Results are based on 1,644 observations (N = 147); $\chi^2(10) = 15.83$, p = .10, CFI = .997, SRMR(WP) = 0.01, SRMR(BP) = 0.02, RMSEA = 0.02.

In addition to examining multilevel factor structure, multilevel SEMs also enable researchers to address questions about dynamic relationships among variables. Similar to multilevel modeling techniques (see Curran & Bauer, 2011, for a review), the dynamic coupling of time-varying variables may be modeled to identify how variations in certain processes (e.g., exercise) coincide with variations in well-being (e.g., on days when one engages in vigorous exercise, one's well-being is higher than on days when one does not). Multilevel SEM provides a more flexible framework to model multivariate relationships among both exogenous and endogenous variables that can be specified at either the within- or between-person levels. As an example of the flexibility of these models, we consider the dynamic relationships between stress, affect, and health. Research has consistently demonstrated a within-person (daily) relationship between stress exposure and affect (e.g., Sliwinski, Almeida, Smyth, & Stawski, 2009). This reactivity to stress (i.e., the within-person slope) has been shown to predict later health outcomes, such that individuals who show a stronger within-person relationship between stress and affect have worse health outcomes than individuals who are less reactive (Piazza et al., 2013). Within a multilevel SEM framework, individual differences in the within-person slope (i.e., random slope effect) can be modeled to account for individual differences in other endogenous variables. Figure 11.2 demonstrates an example of such a model, where the random within-person relationship between daily stress and affect ($s1_i$) accounts for between-person differences in health. There are many other possible models that can be incorporated within a multilevel SEM framework in conjunction with intensive burst designs to address complex questions surrounding the dynamic nature of well-being (e.g., SWB and PWB) and its relationships with other key variables.

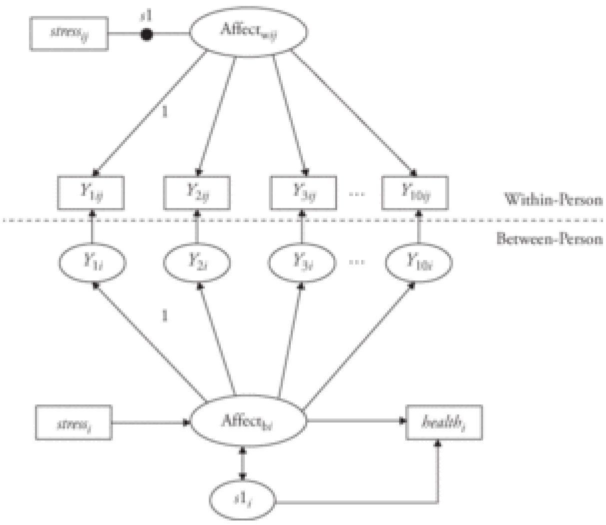

Figure 11.2 Multilevel structural equation model of the within- and between-person relationships between stress, stress reactivity, affect, and health.

Location Scale Models

Intensive measurement designs also provide the opportunity to model variability in new and interesting ways. Often the focus of our analyses is on the level and how this level may differ in relation to other covariates. However, the amount of variability an individual displays may also provide insights into the underlying processes (MacDonald, Hultsch, & Dixon, 2003). Typical multilevel models (mixed-effects models, hierarchical linear models) carry the assumption that the variability an individual expresses is homogenous across time. That is, a single variance value can be computed, such as the intraindividual standard deviation, to (p. 147) indicate the amount of variability in that individual over time. This has been fruitful in research examining the role of variability in predicting other outcomes (e.g., MacDonald, Li, & Bäckman, 2009; Röcke, Li, & Smith, 2009). However, the assumption that variability is homogeneous over time may not always be tenable. The amount of variability an individual expresses may depend on a number of individual or contextual characteristics. Thus, modeling the heterogeneity of the within-person variance (i.e., the variability in the amount of variance over time) and including meaningful covariates to account for why individuals are more variable on some occasions than others is an alternate way to understand process.

Recent attention has been directed to the location scale model, which is an extension of the multilevel modeling framework (Hedeker, Mermelstein, Berbaum, & Campbell, 2009; Hedeker, Mermelstein, & Demirtas, 2008; Rast, Hofer, & Sparks, 2012). The location scale model incorporates both an individual's measured level (location) and their variability around that level (scale). Both the location and the scale are permitted to be random, such that, on any given occasion, an individual may deviate from their typical level and they may also deviate from their typical amount of variability (i.e., may be more or less variable than normal/average). In this way, the location scale model allows the heterogeneity of the variance to be modeled and accounted for with other covariates.

Location scale models have been applied to examine the nature of variability in affect. Hedeker and colleagues (2008) found that adolescent smokers were less variable in their negative affect on occasions when they had smoked compared to occasions when they had not smoked, indicating that the act of smoking had a stabilizing effect on the mood of adolescent smokers. Other research found that individuals were more variable in their affect on occasions when they experienced higher levels of stress relative to occasions when they experienced less stress (Rast et al., 2012). Location scale models can also account for between-person differences in within-person variability. For example, children who engaged in more physical activity on average were shown to have more stable affect (i.e., less intraindividual variability) than children who engaged in less physical activity (Dunton et al., 2014).

Another feature of the location scale model is the ability to model the covariance between level and variability. Individual mean level and the amount of intraindividual variability are often correlated, which can be a result of floor or ceiling effects of measurement, but may also be of substantive interest. Modeling both the level and the variability in (p. 148) the same model adjusts for their effects on each other and also permits the covariance to be examined. Overall, location scale models provide an approach to better understand the individual and contextual factors that may affect the consistency of well-being.

Dynamic Systems Analysis

Another implementation of intensive burst designs is dynamic systems analysis. Fundamentally, a dynamic systems approach offers a way to formalize concepts of self–regulation. The focus is on modeling or representing the relationships between the current state of a variable or an ensemble of variables and the subsequent state of such variables (Boker & Nesselroade, 2002). One key advantage of the dynamic systems approach over other approaches is its capacity to represent "shocks" or other inputs from outside the individual.

For example, consider a model of self-regulation that reflects a “pendulum with friction,” which is hypothesized to best exemplify the intra-individual dysregulation that may result from exposure to daily stress. This model is referred to as a *damped linear oscillator*. The equation for the damped linear oscillator can be expressed as a linear regression formula in which the acceleration of the pendulum is the outcome variable, and the position and velocity of the pendulum are the predictor variables (Boker, 2001). From a developmental perspective, *velocity* may refer to the linear change in the system (e.g., change in mood), and *acceleration* may pertain to the curvature (e.g., the speed with which the mood change occurs). Differential equation models express effects within a system in terms of their derivatives (i.e., the instantaneous rates of change of the variables), as well as in terms of the values of the variables themselves. For example, a differential equation model of emotion regulation following stress might relate daily affect to its slope, or first derivative (i.e., how rapidly an individual’s mood was changing). A more complete model might include effects related to its curvature, or second derivative (i.e., how rapidly mood was accelerating and decelerating in its change). These three parameters—initial position (emotion/affect), velocity (change), and acceleration (speed of change)—represent a dynamic system in which the relationships between parameters define a central tendency of a family of trajectories that any one individual might have (Boker & Nesselroade, 2002). The regression coefficients from this structural equation model, in turn, define order parameters (e.g., frequency and decay rate) of the system that best represent the interrelations between variability in affect and stress over time. The dynamic systems approach is both efficient and powerful, since it can identify intraindividual fluctuations in dynamics using relatively sparse data.

Summary and Conclusions

We have striven to demonstrate in this chapter that positive psychology is a theory with many facets. But to recognize that positive psychology has many facets is merely to start to understand it. Just what are the facets? How do they emerge in culture and in individuals? What are their functions? How do they change and evolve over time? We offer no definitive answers to these questions. Rather, we have attempted to provide a general orienting framework that can guide the thinking of researchers about positive psychological phenomena, sensitize them to the kinds of data that are needed to study these phenomena, and suggest fruitful lines of analyses and interpretation of their effects.

In particular, we have suggested that scientific understanding has moved away from the idea that human well-being can be well represented by a single dimension. Evidence accumulated over the course of this century has made it clear that the phenomenon of human well-being is multidimensional. Therein lies a problem in identifying particularly happy individuals; therein lies a problem of determining where to look for particularly happy individuals; therein lies the difficulty of examining a hypothesis stipulating that, on average, happy people will display more wisdom and character than unhappy people. Jahoda (1958) brought attention to this problem over 50 years ago, and it still does not have a ready solution. The use of eudaimonic indicators solves one problem but introduces another: In what sense is one better off with a higher “purpose in life,” to take one example, if unhappiness accompanies it?

We also have suggested that one major limitation of current theorizing in positive psychology is inherent in the very properties of extant measurement tools. That is, most theories of well-being (SWB and PWB) are described in terms of Cartesian coordinates or factors. These factors may be rotated into an infinity of different positions, each equally adequate for describing the relationships among dimensions of well-being, but each calling for different concepts and different language for describing human well-being. A meta-theory of simple structure has guided the rotation that has been accepted as the basis (p. 149) structure of SWB and PWB theory. This meta-theory requires that manifest dimensions of well-being relate to a finite number of factors. This is a reasonable requirement for studies designed to indicate it—and many studies have been so designed—but it is not an indication of how well-being *must* be organized to account for relationships that are observed within and across individuals.

Finally, we have underscored the importance of taking a process approach to understanding the complexity of positive human health and well-being. Extant theories of SWB and PWB provide few details about how well-being develops or about how positive psychological states interact and work together to produce optimal human functioning. These theories, therefore, do little to indicate the dynamics of human adaptation. The kind of system that ultimately will best describe such adaptation and its development, we submit, will be functional and will map on to the human brain. Over time, such a system might be more nearly of the form of a spiral of Archimedes, out of which evolves a repetitive building on what is known (induction), which leads to deductions that generate empirical studies and more induction, which lead to further deductions, which spawn further induction, and so on. In the long run, knowing that science is a never-ending search for better explanations and that no theory of reality is final, we can be confident that SWB and PWB theory will be replaced by a better theory.

Future Questions

1. How is positive health and well-being organized across individuals and within individuals across time?
2. How does positive health and well-being develop and change across the lifespan?
3. How do individual differences in within-person changes in positive health and well-being come about?

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