The New Person-Specific Paradigm in Psychology

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ABSTRACT—*Most research methodology in the behavioral sciences employs interindividual analyses, which provide information about the state of affairs of the population. However, as shown by classical mathematical-statistical theorems (the ergodic theorems), such analyses do not provide information for, and cannot be applied at, the level of the individual, except on rare occasions when the processes of interest meet certain stringent conditions. When psychological processes violate these conditions, the interindividual analyses that are now standardly applied have to be replaced by analysis of intraindividual variation in order to obtain valid results. Two illustrations involving analysis of intraindividual variation of personality and emotional processes are given.*

KEYWORDS—*interindividual variation; intraindividual variation; ergodic conditions; R-technique; P-technique; Big Five Personality Factors; emotional experiences*

During the past century, data analysis of psychological processes has mainly been conducted using methods that focus on variation between subjects. Such variation—that is, interindividual variation—is used to derive statistics (e.g., means, correlations) that characterize states of affairs in the population of subjects. The statistics concerned are derived by pooling across subjects—this is the hallmark of analyses of interindividual variation. All standard statistical methods focus on analysis of interindividual variation, regardless of whether the data are gathered cross-sectionally, longitudinally, or according to a multilevel design.

It might seem evident that inferences about the state of affairs at the population level constitute general findings that apply to each individual subject in the population. However, applying the findings obtained by pooling across subjects to a single individual in the population involves a shift in level—namely, from the level of interindividual variation to that of *intra*individual variation in time and place. Is this shift between levels valid? It will be shown that, generally speaking, the answer is no. This is directly evident when applying general mathematical-statistical theorems—the so-called classical ergodic theorems. These are the first theorems (hence classical) that in the early 1930s were derived in ergodic theory, a branch of mathematics originally motivated by problems of statistical physics.

In what follows, we give a heuristic description of the ergodic conditions under which scientific findings based on interindividual variation can be applied to an individual subject. It will also be shown that these conditions are strict and therefore are rarely met. This reality has wide-ranging consequences for psychological methodologies and statistical analyses that are intended to inform individual treatment and policy. In this article, we suggest that substantial methodological changes must be made in order to successfully avoid the pitfalls in analyzing psychological processes that violate the ergodic conditions. Such changes may require a Kuhnian paradigm shift within the science of psychology.

CONDITIONS FOR ERGODICITY

Ergodicity addresses the following fundamental question: Given a particular set of selected variables, under which conditions will an analysis of interindividual variation—an analysis in which information is pooled across subjects—yield the same results as an analysis of intraindividual variation? To contrast analyses of interindividual variation with analyses of intraindividual variation, it is helpful to conceive of a human being as an integrated dynamic system of behavioral, emotional, cognitive, and other psychological processes evolving over time and place. These processes of the individual can be tapped with various psychological measures across different time points. Following Cattell's (1952) illustration of the various dimensions of psychological data, we can conceive of a plane of measureable elements, of which time is one dimension and psychological variables constitute the other dimension. If we then add multiple

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subjects as a third dimension, we have the three-dimensional Cattell data box (Fig. 1).

Using the Cattell data box to illustrate intraindividual variation analyses, we focus on a single subject (a horizontal slice of the box) and select a range of time points (occasions) and various psychological measures (variables). We have thus selected a single individual's system of psychological variables across time and can determine the variation of the scores of these variables by pooling across time; an analysis of intraindividual variation is known as P-technique, and is represented in Figure 1 as a horizontal slice of the box (Cattell, 1952). In contrast, interindividual variation is illustrated by selecting one or a few fixed time points as measurement occasions, selecting a subset of variables, and pooling across subjects. Interindividual analysis is known as R-technique and is represented in Figure 1 as a vertical slice of the box (Cattell, 1952).

Rephrasing the question, "Under which conditions will an analysis of interindividual variation yield the same results as an analysis of intraindividual variation?", we can ask, "When does R-technique yield results equal to those of P-technique?" The classical ergodic theorems provide the following general answer: "Only if the data obey two rigorous conditions" (cf. Molenaar, 2004; Molenaar, Huizenga, & Nesselroade, 2003). First, the same statistical model should apply to the data of all subjects in the population (homogeneity of the population). Second, the data must be stationary—that is, the data must have invariant statistical characteristics across time, for instance, having constant mean and variance. Further elaborations on the conditions of homogeneity and stationarity will be given shortly. However, it is important to note that in cases where either one (or both) of these two conditions is not met, the psychological process concerned is nonergodic—that is, its structure of interindividual variation will differ from its structure of intraindividual variation. For all nonergodic processes, the results obtained in standard analysis of interindividual variation do not apply at the level of intraindividual variation, and vice versa.

Condition 1: Homogeneity

The first condition for ergodicity is that each subject in the population has to obey the same statistical model (homogeneity of the population). This means that the main features of a statistical model describing the data are invariant across subjects. Consider the case of a factor model in which factors represent common constructs explaining the correlation between observed variables. For example, in a one-factor model for an intelligence test composed of several items, the factor represents general intelligence and explains the correlations between the item scores. The regression weights indicating the strength of the relationships of observed variables with the factors are called factor loadings. The homogeneity condition for ergodicity implies that the number of factors and the factor loadings must be invariant across subjects. Only then can a factor model of the population (R-technique) be validly applied to an individual subject (P-technique). For example, an intelligence test could measure general intelligence for some subjects but verbal and visual intelligence for others; also, the strength of the relationships of items with general intelligence could differ between

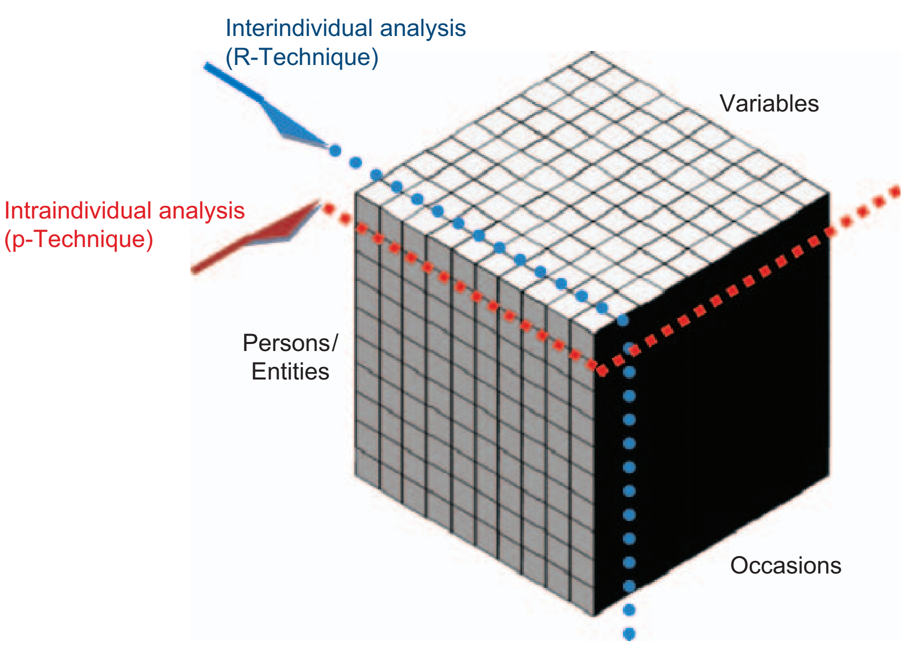

Fig. 1. The Cattell data box (see Ram & Nesselroade, 2007), emphasizing that any datum is simulataneously defined as an intersection of Person, Variable, and Occasion coordinates. Interindividual (R-technique) and intraindividual (P-technique) data constitute particular ''slices'' of the data box as indicated.

subjects. In such cases the homogeneity condition for ergodicity is violated.

An empirical example of a non-ergodic factor model is illustrated in a factor analysis of repeatedly measured scores on a personality test obtained by Borkenau and Ostendorf (1998; the reader is referred to their article for a detailed description of the study). The replicated-time-series design they used involves 22 subjects measured on 90 consecutive days with (equivalent versions of) the same questionnaire composed of 30 items (6 items for each Big Five personality factor: Neuroticism, Extraversion, Agreeableness, Conscientiousness, Intellect). It is found in standard analysis of interindividual variation (R-technique) that these Big Five personality factors indeed explain the correlations between the 30 item scores.

However, it is found in separate analyses of intraindividual variation (P-technique) that the Big Five personality factors do not explain the correlations between the 30 repeatedly measured item scores of each individual subject. Table 1, Part A, presents the obtained nominal Big Five factor model (R-technique). The 30 items are specified in the far left column and the five factors are presented across the top by their nominal descriptions. Substantial factor loadings (over .50) of each of the items onto the five factors obtained are presented by an *x*.

In parts b, c, and d of Table 1, P-technique factor models for each of three individual subjects (Subjects 13, 1 and 8, respectively) are presented. These three P-technique models were chosen from the total 22 as clearly representative of the range of obtained models. As illustrated, none of the three intraindivid-

TABLE 1

Model of the Relationship Between Specific Traits and the Big Five Factors of Personality for the General Population (A) and Intraindividual Models for Three Representative Subjects (B, C, and D)

						Intraindividual models (3 subjects)								
	Interindividual model (A)					(B)			(C)				(D)	
Trait adjective	Neuroticism (N)	Extraversion (E)	Agreeableness (A)	Conscientiousness (C)	Intellect (I)	F1	F2	F3	F1	F2	F3	F4	F1	F2
irritable	x					x				x			x	
vulnerable	x					x				x			x	
emotionally stable	x					x				x			x	
calm	x					x				x			x	
resistant	x					x				x			x	
changeable	x					x			x				x	
dynamic		x						x						
sociable		x						x					x	
lively		x						x				x		
shy		x						x						
silent		x						x				x	x	
reserved		x						x				x		
bad-tempered						x			x				x	
good-natured			x			x			x				x	
helpful			x						x					
considerate			x			x			x				x	
selfish			x			x								
domineering			x			x			x					
obstinate			x			x			x					
industrious				x			x							x
persistent				x										
responsible				x					x					
lazy				x			x		x					x
reckless									x					
witty					x						x			
knowledgeable					x		x				x			x
prudent					x		x				x			
fanciness					x						x			
uninformed					x		x				x			
unimaginative					x		x				x			x

Note. In (A), *x*s represent personality items with +/− factor loadings greater than .50 (reconstructed after Timmerman, 2001). For the intraindividual models (B,C,D), *x*s represent personality items with +/− correlations between items and factors—an equivalent to a factor loading—greater than .50 (intraindividual solutions reconstructed after Hamaker, Dolan, & Molenaar, 2005).

ual factor models presented correspond to the interindividual nominal Big Five-factor model, and this is in fact the case for the other 19 intraindividual models. The P-technique factor model for subject 13 has three factors, the factor model for subject 1 has four factors, and the factor model for subject 8 has two factors. Once again, *x* represents substantial factor loadings for each item on the obtained factors.

We have here an example clearly violating the homogeneity condition for ergodicity: The intraindividual models differ between subjects not only in the number of factors but also in how the factors relate to the items (as expressed by the patterns of factor loadings). Because the measured personality process violates the condition of homogeneity, it is non-ergodic, and therefore the nominal interindividual (Big Five) structure cannot be generalized to the level of variation within each subject. Consequently, one cannot expect that the correlations between repeatedly measured items scores of an individual subject can be explained by the factors Neuroticism, Extraversion, Agreeableness, Conscientiousness, and Intellect.

Condition 2: Stationarity

The second condition for ergodicity is that a psychological process should have constant statistical characteristics in time (stationarity)—meaning that the statistical parameters of the data (factor loadings, etc.) should remain invariant across all time points. Prime examples where this condition is violated are developmental processes, which almost by definition have statistical characteristics that change over time. For instance, the factor loadings explaining associations among intelligence subtests measuring Visual and Verbal intelligence change during development (as can be evaluated by means of appropriate likelihood-ratio tests). Learning, habituation, transient brain responses, and many more psychological processes also are nonstationary—the associations among variables characterizing these processes change in time. When psychological processes violate the stationarity criterion for ergodicity, their inter- and intraindividual structures of variation differ.

The proper way to analyze nonstationary (hence non-ergodic) psychological processes is by means of special variants of P-technique, which have become available only recently (Molenaar, Sinclair, Rovine, Ram, & Corneal, 2009). To illustrate the application of the newly developed model for nonstationary time series, data were taken from a study of the emotional experiences of sons (age range 14–18 years) as they interacted with their fathers over time. Data collection lasted for a period of 6 to 8 weeks, or until 80 interactions had occurred, with sons completing measures of both positive and negative emotions following each interaction.

Focusing on a single participant, P-technique factor analysis results in a three-factor model, the factors being interpreted as (a) Involvement, with substantial factor loadings for items such as interest, determination, and enthusiasm; (b) Anger, with substantial factor loadings for distress, irritation, and not getting what one wants; and (c) Anxiety, with substantial factor loadings for being nervous, jittery, or scared. As will be shown, these data indicate a non-ergodic psychological process for which standard analysis of interindividual variation is inappropriate (cf. Molenaar, Sinclair, Rovine, Ram, & Corneal, 2009; for further details and additional results).

Application of the new P-technique time-series model to the Involvement variable shows the value of Involvement at each subsequent interaction episode (t + 1) as a function of Involvement, Anger, and Anxiety at the preceding interaction episode (t). Figure 2 illustrates these relationships over time. The dynamic relationship between Anxiety and subsequent Involvement can be observed by focusing on the line corresponding to the variable Anxiety. The line depicts the changing relationship between Anxiety at a specified time point (t) and Involvement at the next interaction episode (t + 1). As depicted, the relationship between Anxiety and subsequent Involvement changes from a negative relationship, −.20, at the start of the observation interval, to a positive relationship, .20, at about interaction number 45, and then decreases slightly again. In other words, at the start of the observation interval, an increased value of Anxiety leads to a decrease in the value of subsequent Involvement, whereas in the second half of the observation interval, an increased value of Anxiety leads to an increase in the value of subsequent Involvement.

This new method allows for examination of psychological processes that are nonstationary and thus non-ergodic. In the past, analyses of such processes could only be accomplished at the population level, resulting in a trajectory for the "average" individual, obtained by pooling across subjects. As this article demonstrates, application of the average trajectory to any one individual is usually invalid. Thus, scientific study of such

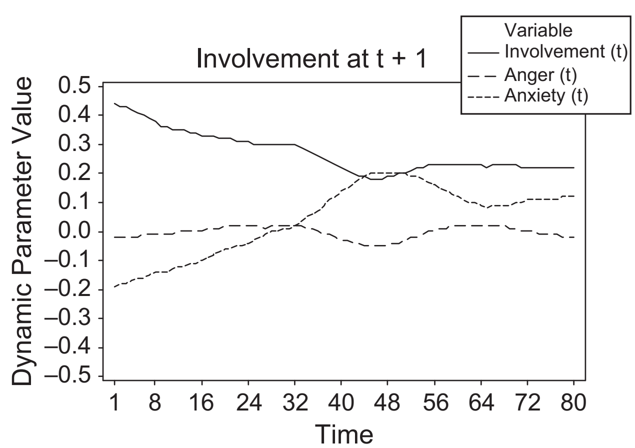

Fig. 2. Time-varying regression weights (parameter value) indicating the strength of the relationship between subsequent involvement (Involvement t + 1), and preceding Involvement, Anxiety, and Anger (at time t) in a biological son's emotional experiences interacting with his father over 80 interactions.

processes has to be based on analysis of intraindividual variation, using methods such as those described here.

DISCUSSION AND CONCLUSION

Psychological processes like cognitive information processing, perception, emotion, and motor behavior occur in real time at the level of individual persons. Because they are person-specific, these processes differ from variables occurring in a population of human subjects—variables such as sex, socioeconomic status, or experimental condition (so called between-subject variables). Much psychological research is concerned with variation at the level of the population. However, whenever person-specific processes are involved, and in so far as these processes are non-ergodic (i.e., obey person-specific dynamic models and/or have nonstationary statistical characteristics), their analysis should be based on intraindividual variation.

Using new analytical methods that have become available, it is now possible to study variation at the level of individual subjects across time. One valuable product of this necessary adjustment involves the possibility to optimally guide the psychological processes concerned. The time-series models obtained in analyses of intraindividual variation can be used to carry out feedback-feedforward guidance in real time. For instance, we are studying person-specific optimal guidance of daily treatment of diabetes and asthma. Whereas interindividual methods have established guidelines for pharmaceutical dosages for groups of individuals with similar physiological characteristics (such as body weight), new intraindividual methods can establish more accurate person-specific optimal dosages. In principle, the modeling of intraindividual variation associated with any psychological process may be used to implement optimization techniques that can guide that process to desirable levels and keep it there for the continuous benefit of each individual person in his or her time-varying unique life situation.

We are at the brink of a major reorientation in psychological methodology, in which the focus is on the variation characterizing time-dependent psychological processes occurring in the individual human subject. It will require substantial efforts from the community of psychological scientists to effectuate this reorientation. At present, there is very little literature on multivariate time-series designs and analysis techniques tailored to dealing with non-ergodic psychological processes. An additional problem lies in the lack of established curricula to teach students of psychology in state-of-the-art statistical techniques and methodologies for the analysis of intraindividual variation. Several research centers collaborating within the Developmental Systems Group[1] are in the process of initiating new teaching and research projects focused on intraindividual variation of cognitive, emotional, and personality processes. Legitimate generalization to the wider population is then achieved through identification of subsets of similar individuals. Given the finding that interindividual variation often cannot be equated to intraindividual variation, the dedicated study of intraindividual variation is, in view of the classical ergodic theorems, no longer an option, but a necessity.

[1]Additional information about the Developmental Systems Group can be obtained from the authors.

Recommended Reading

Borsboom, D. (2005). *Measuring the mind: Conceptual issues in contemporary psychometrics*. Cambridge, UK: Cambridge University Press. Addresses the issue of non-ergodicity in the context of psychometrics.

Hamaker, E.J., Dolan, C.V., & Molenaar, P.C.M. (2005). (See References). A thorough, far-reaching theoretical analysis of intraindividual variation.

Molenaar, P.C.M. (2004). (See References). The earliest paper addressing the issue of non-ergodicity.

Molenaar, P.C.M. (2008). Consequences of the ergodic theorems for classical test theory, factor analysis, and the analysis of developmental processes. In S.M. Hofer & D.F. Alwin (Eds.), *Handbook of cognitive aging* (pp. 90–104). Thousand Oaks, CA: Sage. A highly accessible, comprehensive overview of the issues of non-ergodicity and analysis of intraindividual variation.

Nesselroade, J.R., Gerstorf, D., Hardy, S.A., & Ram, N. (2007). Idiographic filters for psychological constructs. *Measurement*, *5*, 217–235. Provides a more detailed discussion of non-ergodicity and analysis of intraindividual variation.

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REFERENCES

Borkenau, P., & Ostendorf, F. (1998). The Big Five as states: How useful is the five-factor model to describe intra-individual variations over time? *Journal of Personality Research*, *32*, 202–221.

Cattell, R.B. (1952). The three basic factor-analytic designs: Their interrelations and derivatives. *Psychological Bulletin*, *49*, 499–520.

Hamaker, E.J., Dolan, C.V., & Molenaar, P.C.M. (2005). Statistical modeling of the individual: Rationale and application of multivariate stationary time series analysis. *Multivariate Behavioral Research*, *40*, 207–233.

Molenaar, P.C.M. (2004). A manifesto on psychology as idiographic science: Bringing the person back into scientific psychology, this time forever. *Measurement*, *2*, 201–218.

Molenaar, P.C.M., Huizenga, H.M., & Nesselroade, J.R. (2003). The relationship between the structure of interindividual and intraindividual variability: A theoretical and empirical vindication of Developmental Systems Theory. In U.M. Staudinger & U. Lindenberger (Eds.), *Understanding human development: Dialogues with life-span psychology* (pp. 339–360). Dordrecht, the Netherlands: Kluwer.

Molenaar, P.C.M., Sinclair, K.O., Rovine, M.J., Ram, N., & Corneal, S.E. (2009). Analyzing developmental processes on a individual level using non-stationary time series modeling. *Developmental Psychology*, *45*, 260–271.

Ram, N., & Nesselroade, J.R. (2007). Modeling intraindividual and intracontextual change: Operationalizing developmental contextualism. In T.D. Little, J.A. Bovaird, & N.A. Card (Eds.), *Modeling contextual effects in longitudinal studies* (pp. 325–342). Mahwah, NJ: Erlbaum.

Timmerman, M.E. (2001). *Component analysis of multisubject multivariate longitudinal data*. Unpublished doctoral dissertation, University of Groningen, Groningen, the Netherlands.