APPLYING IDIOGRAPHIC RESEARCH METHODS: TWO EXAMPLES

Wayne Velicer
Cancer Prevention Research Center, University of Rhode Island, United States of America
velicer@uri.edu

Idiographic methods focus on time-dependent variation within a single individual (intra-subject variability) in contrast to group-level relationships (inter-subject variability) that may yield different results. Equivalent results occur only if two, probably unrealistic, conditions specified by Ergodic Theorems are met: (1) Each trajectory follows the same dynamic laws, and (2) Each trajectory has equal mean levels and serial dependencies. Two studies illustrate the difficulty of meeting ergodic conditions and unique types of research questions that can be addressed by idiographic methods. The first example involves longitudinal smoking patterns. The second study involves reactions of autistic students to environmental stressors. Neither study supports the ergodic conditions. Both studies illustrate research questions unique to idiographic methods, which produce information that is likely to be distinct from that provided by group-based methods.

INTRODUCTION

Time series analysis (Velicer & Fava, 2003) is important in longitudinal statistical designs, sometimes called idiographic designs. Such designs typically involve single subjects or research units, which are measured repeatedly at regular intervals over a large number of observations. Time series analysis can be viewed as the exemplar of a longitudinal design. A time series analysis can help us to understand the underlying naturalistic process, the pattern of change over time, or evaluate the effects of either a planned or unplanned intervention. Advances in information systems technology, such as telemetrics (Goodwin, Velicer, & Intille, 2008) are making make time series designs an increasingly feasible method for studying important psychological phenomena.

Modern time series analysis and related research methods represent a sophisticated leap forward in the ability to analyze longitudinal data. Early time series designs in psychology relied heavily on graphical analysis to describe and interpret results. While graphical methods are useful and provide important ancillary information, the ability to bring a sophisticated statistical methodology to bear on this class of data has revolutionized the area of idiographic research.

Time series analysis is an example of a class of research methods called idiographic methods. Idiographic methods focus on the time-dependent variation within a single individual or unit (intra-subject variability) in contrast to methods which focus on group-level relationships (inter-subject variability). An inter-individual analysis may yield different results than an intra-individual analysis. Equivalent results will occur only if the two conditions specified by the Ergodic Theorems are met: (1) Each individual trajectory has to obey the same dynamic laws, and (2) Each individual trajectory must have equal mean levels and serial dependencies. These theorems are unlikely to be met in practice but we have seldom had data adequate to test this. More fundamentally, idiographic methods (Molenaar, 2003) can address different research questions than nomothetic or group level methods, and may provide more insight into the data.

In this paper, I first present a brief overview of some of the important issues in employing idiographic methods. Then I present two examples from the literature that describe the extent to which the ergodic theorems are likely to be met in practice. These examples also serve to illustrate the alternative types of research questions that can be addressed by idiographic methods.

Overview of Idiographic Methods

Time series analysis and other idiographic methods have been more generally developed in areas such as engineering and economics before they came into widespread use within social science research. The prevalent methodology that has developed and been adapted in psychology is the class of time series models known as Autoregressive Integrated Moving Average (ARIMA) models (Box & Jenkins, 1976; Box & Tiao, 1975; Box, Jenkins, & Reinsel, 1994). Time series analysis belongs to the class of new methods of data analysis that require the use of modern high-speed computers. Estimation of basic parameters cannot be performed by pre-computer methods.

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A major characteristic in most time series is the inherent *dependency* present in a data set that results from repeated measurements over time on a single subject or unit. All longitudinal designs must take the potential relationship between observations over time into account. For time series analysis, the dependency precludes the use of traditional statistical tests. An important assumption for statistical testing, independence of the error in the data, is usually not met. ARIMA models are especially useful for time series analysis as they can model the effects of dependency from the data series (Glass, Willson, & Gottman, 1975) and allow valid statistical testing.

One advantage of idiographic methods is that they can be used in *applied settings*, such as businesses, schools, clinics and hospitals. More traditional between-subject research designs may not be the most appropriate, or, in some instances, impossible to implement in such settings. In some cases, data appropriate for time series analysis is generated on a regular basis in the applied setting, like the number of hospital admissions. In other cases, a complete understanding of the process that can explain the acquisition or cessation of an important behavior may require the intensive study of an individual over an extended period of time. The advances in information systems technology have facilitated the repeated assessment of individuals in natural settings.

Idiographic methods have important advantages over other procedures for investigating *patterns of change* across time. These patterns can be quite varied and some questions that can be investigated in this context include: (a) Are intervention effects temporary or permanent; (b) Does the intervention cause a change in the 'slope' of the behavior process as well as the overall level; (c) Does the intervention cause a change in any cycling that is present in the underlying behavior process; (d) Does the intervention cause the variance to change; and (e) Does the intervention cause a change in the nature of the dependency that is present in the time series process?

An important issue for idiographic methods is whether results can be generalized. For idiographic research, generalizability can not be inferred from a single study. Researchers need to engage in systematic replication to demonstrate generalizability. Second, traditional measures used in cross-sectional studies in many content areas may not be appropriate for idiographic designs. For time series analysis, the best measures are those that can be repeated a large number of times on a single subject at intervals of short duration. An even more basic concern is whether generalizability to the group level should always be viewed as an important goal. Generalizability within an individual or unit over time may be the primary goal of the research.

EXAMPLE 1: LONGITUDINAL PATTERNS IN A NICOTINE HARM REDUCTION STUDY

Hoeppner, Goodwin, Velicer, Mooney and Hatsukami (2008) examined daily smoking rates following the end of an intensive smoking reduction program. The primary study evaluated the relationship of tobacco biomarkers with reduced levels of smoking (Hatsukami et al., 2005). The sample analyzed involved a subset of 151 active smokers recruited for the study. The original study consisted of three phases: baseline, reduction, and maintenance. This Hoeppner et al. (2008) follow-up study focused on the 6 week-long maintenance phase. Only 57 participants completed daily records for the first 40 days of the maintenance phase and they were the focus of this study.

The study involved two phases. In the first phase, the timeline of cigarettes smoked per day was plotted for each participant, and the series was analyzed using time series analysis. The intercept, serial dependence, variance, and the linear trend parameters (i.e., slope) were estimated for the number of cigarettes per day for each individual. On average, the 57 participants started the maintenance phase with a daily smoking rate of 7.85 cigarettes per day. Approximately half of the participants (50.9%) had significant first-order autoregressive parameters, and 17.5% had significant second-order autoregressive parameters. The autoregressive parameters for daily smoking rates were generally positive on average, ranging from -0.47 to 1.09 and the first-order autoregressive parameter estimates averaged 0.56. Linear trends were significant for more than half of the sample (59.6%), indicating that there were significant changes in smoking rates over time. Of particular note is the fact that both positive and negative trends were observed. Of the statistically significant slope parameters, the majority were positive (58.8%), indicating an increase in the number of cigarettes smoked per day after the conclusion of the cigarette reduction program. However, a substantial portion of the statistically significant slope parameters were negative (41.2%), indicating a continuing decline over the maintenance phase.

The second phase applied a dynamic typology analysis to the results of the time series analysis in order to determine if homogeneous subgroups existed. A dynamic typology is a cluster analysis applied to longitudinal data. Cluster analysis classifies units based on the level, scatter, and shape of the variables used for clustering. The analysis was performed using the squared Euclidean distance metric and Ward's minimum variance algorithm. Several methods were used to determine the number of clusters resulting in a parsimonious 3-cluster solution representing three distinct types of maintenance patterns: (a) Increasing (47.4%), (b) Constant (12.3%), and (c) Decreasing (40.4%). These descriptive labels correspond to the slope parameters estimated in the individual time series analyses. Figure 1 illustrates the three dynatype clusters and the overall average trajectory across the 57 subjects. Results of this study demonstrate that an idiographic approach yields different findings from those in a group level analysis. Group level analyses would conclude that subjects who achieved a 75% decrease in the number of cigarettes smoked were able to maintain that level. Idiographic analysis reveals that that conclusion is only accurate for a small minority of smokers (12.5%). The two larger groups were the increasing group, who were tending towards returning to their previous level of smoking and the decreasing groups, who were tending towards smoking cessation. A very important new research question is how we can predict group membership and then develop interventions for the increasing group to prevent their regression.

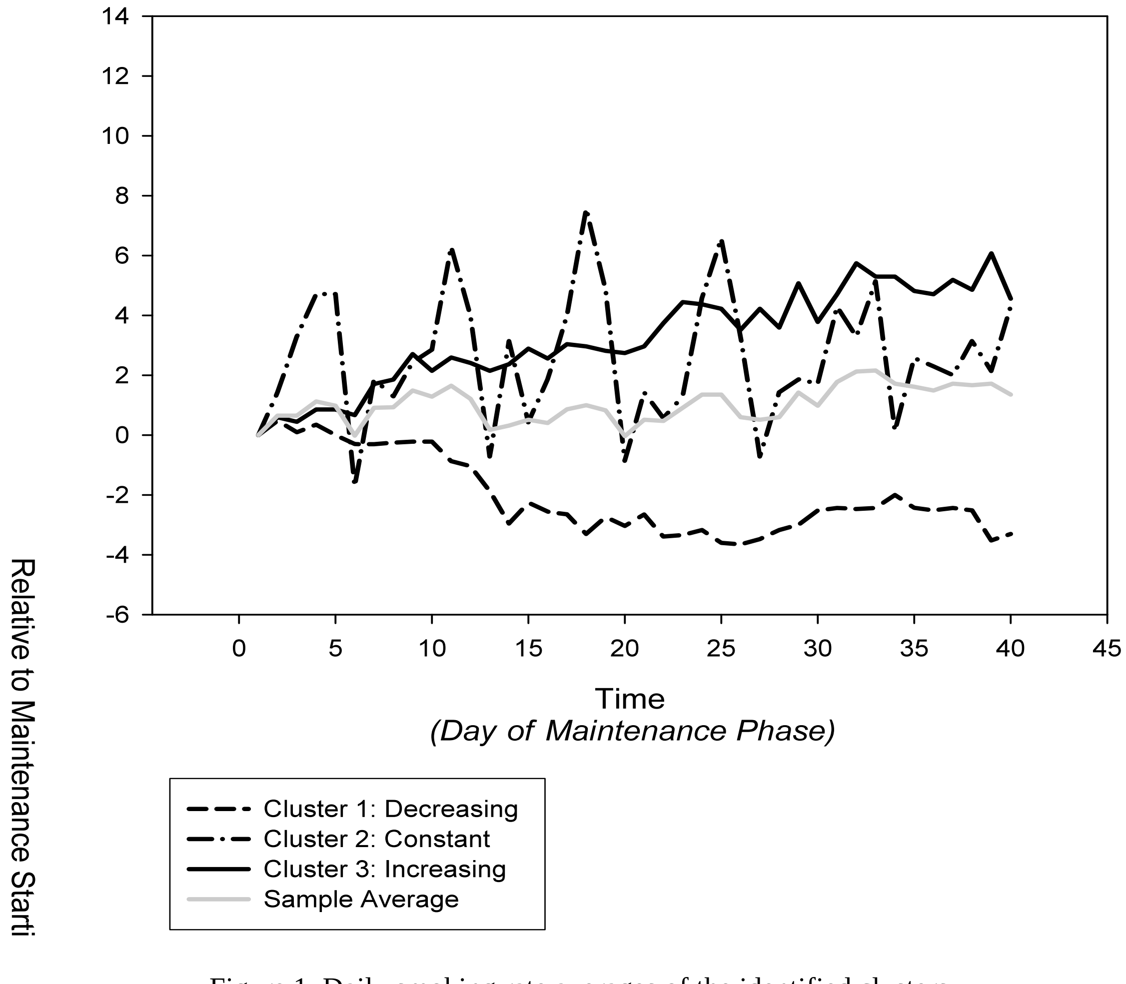

Figure 1. Daily smoking rate averages of the identified clusters,
adjusted for person-specific initial smoking rate in the maintenance phase

From the perspective of the ergodic theorems, it is clear that neither theorem was satisfied. The autocorrelations varied widely, a clear violation of the first theorem and the trajectories clearly did not have the same statistical characteristics, a clear violation of the second theorem. For this example, the idiographic approach is providing different results from the group level analysis.

EXAMPLE 2: AROUSAL IN CHILDREN WITH AUTISM

Goodwin, Groden, Velicer, Lipsitt, Baron, Hofmann, and Groden, (2006) employed telemetric methods to evaluate the degree of reactivity to different types of stressors in children with autism. This is a disorder that affects about 1 in 500 children. Stress is a difficult problem to study with this population since self report is often unreliable or may not be available. In this study, a Lifeshirt System was employed to measure heart rate.

There were two groups of participants. The first consisted of five males with autism, age 8-18, who had been diagnosed with moderate to severe autism. A second group of 5 typically developing individuals were chronologically matched. The study design was a multiple intervention time series design with seven interventions and resting periods before and between interventions. Six of the interventions involved different type of potential stressors such as a loud noise, a difficult task, or a stranger in the room. The last intervention was a vigorous physical activity that provided a validity check on the heart rate measure.

Figure 2 presents two examples. In the first, there was a significant increase in heart rate for two potential stressors, *Eating a Preferred Food* and a *Difficult Task*, as well as the physical activity. In the second, there was a significant increase in heart rate for two potential stressors, an *Unanticipated Object* and *Unstructured Time*, as well as the physical activity.

Responses were different for each individual. Results were also different from the main hypothesis of the study. Autistic groups responded to 22% of the potential stressors and typically developing groups responded to 60% of the stressors. The autistic group had a much higher heart rate, perhaps creating a ceiling effect. Both findings are new and have important implications. Data once again failed to support either ergodic theorem. Stress responses can guide programming for autistic individuals and group level averages would not be useful for this purpose.

DISCUSSION: RESEARCH ISSUES IN IDIOGRAPHIC RESEARCH

There are five major challenges for researchers employing idiographic methods. The first is the issue of generalization. Group methods attempt to generalize findings to all members of a defined population. Idiographic methods cannot use statistical inference as a method of generalization since each person is viewed as unique. One potential solution is systematic replication. However, this approach ignores the individual. Methods that result in an intermediate level of generalizability, such as the attempt to identify homogeneous groups based on similar patterns of change over time (illustrated by the first example), represents an intermediate compromise. However, the question of whether generalizing across individuals is a meaningful question is illustrated by the second example. The individual level analysis provides a direct answer to the question of interest and generalization to the group level would serve no practical purpose. In this case, generalization within the individual over time is the primary issue.

The second issue concerns missing data. When a single unit is studied for a long series of observations, missing data is almost inevitable. A partial solution is to automate data collection as much as possible. An example of this was the computer chip contained in the PAP device that automatically recorded and time stamped whenever the device was employed. Another solution is to employ the very accurate missing data procedures that have been developed over the last three decades like maximum likelihood and multiple imputation (Schafer, & Graham, 2002). Recent simulation studies suggest that these methods can produce very accurate results even when up to 40% of the data is missing and assumptions have been violated (Velicer & Colby, 2005a, 2005b).

The third issue involves identifying the generating functions. Idiographic data permits us to study the generating function that produces the types of data that we are observing. This is an emerging research area with few good examples at present. Identification of the function can be based on the autocorrelation structure as Velicer, Richmond, Greeley, Swift, and Redding (1992) did in an attempt to determine the most appropriate nicotine regulation model for smoking behavior. The nature of the function can be important for intervention development.

The fourth issue involves the development of appropriate measures. The widely used measures in the behavioral sciences are not appropriate for regular assessment at short intervals. Among the problems are recall bias, measure reactivity, and measure pollution. Advances in information systems technology have permitted the development of telemetrics (Goodwin et al., 2008) which represents a promising new approach to developing appropriate measures.

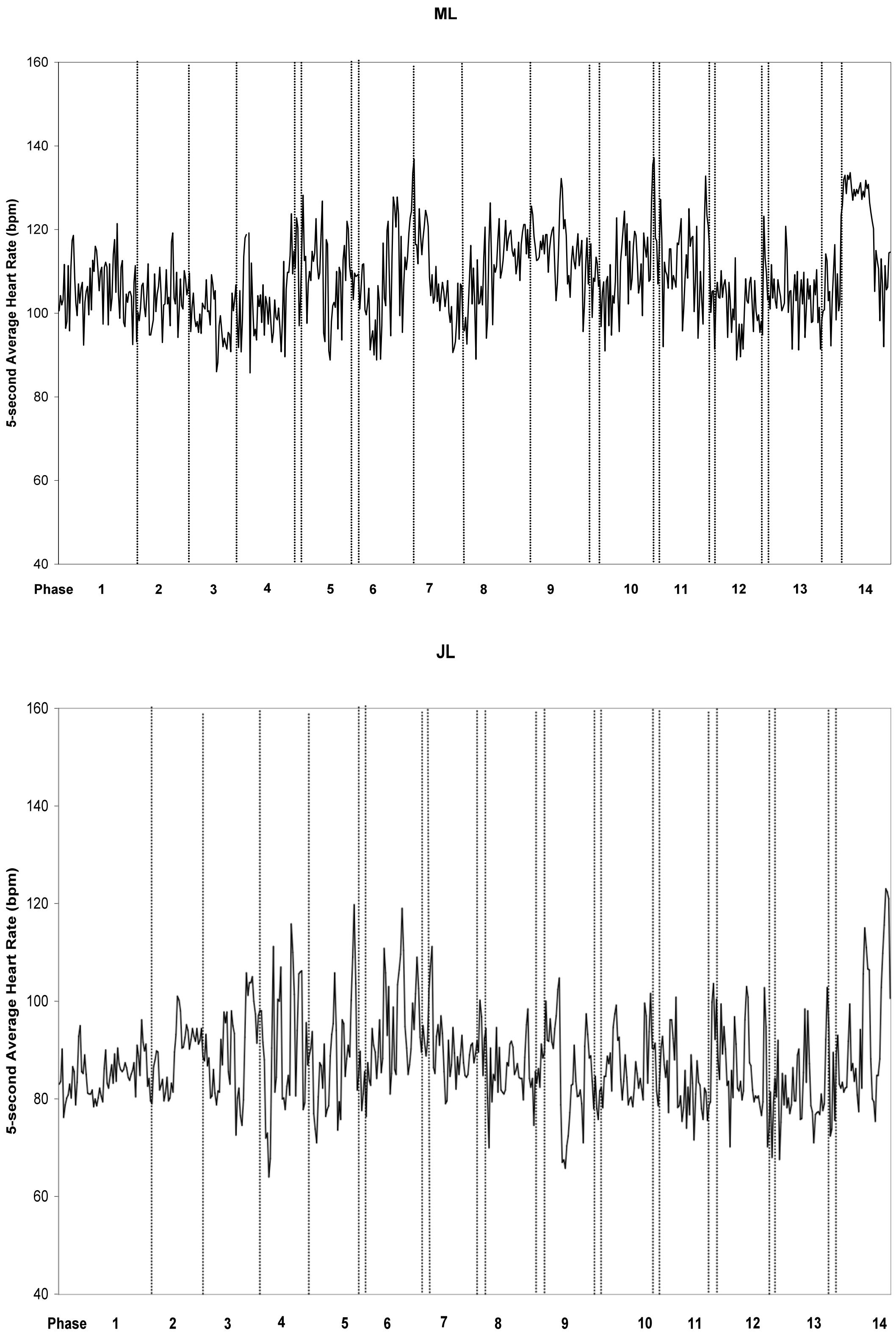

Figure 2. Two Examples of Heart Rate Reactivity to Different Types of Stressors

The fifth issue involves developing an understanding of the implications of the ergodic theorems (Choe, 2005; Molenaar, 2008). The examples presented here suggest that ergodic conditions are unlikely to be met in practice. Most group level data have not included an adequate amount of longitudinal data to test these theorems directly. However, the assumption of the additive constant is a basic assumption of most widely used group level methods and it may not be valid. Indeed it seems unlikely that most subjects will react to most interventions in an exactly similar manner. If this is true, it suggests that a focus on the individual rather than groups is critical for future research and the development of interventions.

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REFERENCES

Box, G. E. P., & Jenkins, G. M. (1976). *Time-series analysis: Forecasting and control*. San Francisco: Holden Hay.

Box, G. E. P., Jenkins, G. M., & Reinsel, G. C. (1994). *Time series analysis: Forecasting and control* (3rd Ed.) Englewood Cliffs, NJ: Prentice-Hall, Inc.

Box, G. E. P., & Tiao, G. C. (1975). Intervention analysis with application to economic and environmental problems. *Journal of the American Statistical Association, 70,* 70-92.

Choe, G. H. (2005). *Computational ergodic theory*. Berlin: Springer.

Glass, G. V., Willson, V. L., & Gottman, J. M. (1975). *Design and analysis of time series experiments*. Boulder, CO: Colorado Associate University Press.

Goodwin, M. S., Groden, J., Velicer, W. F., Lipsitt, L. P., Baron, M. G., Hofmann, S. G., & Groden, G. (2006). Cardiovascular arousal in individuals with autism. *Focus on Autism and Other Developmental Disabilities*, *21*, 100-123.

Goodwin, M. S., Velicer, W. F., & Intille, S. S. (2008). Telemetric monitoring in the behavior sciences. *Behavior Research Methods, 40*, 328-341.

Hatsukami, D. K., Kotlyar, M., Allen, S., Jensen, J., Li, S., Le, C., et al. (2005). Effects of cigarette reduction on cardiovascular risk factors and subjective measures. *Chest*, *128*(4), 2528-2537.

Hoeppner, B., Goodwin, M., Velicer, W. F., Mooney, M. E., & Hatsukami, D. K. (2008). Detecting longitudinal patterns of daily smoking following drastic cigarette reduction. *Addictive Behaviors, 33*, 623-639.

Molenaar, P. C. M. (2003). A manifesto on psychology as an idiographic science. *Measurement, 4*, 201-218.

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: Sage.

Schafer, J. L., & Graham, J. W. (2002). Missing data: Our view of the state of the art. *Psychological Methods, 7*, 147-177.

Velicer, W. F., Richmond, R., Greeley, J., Swift, W., & Redding, C. R. (1992). A time series investigation of three nicotine regulation models. *Addictive Behaviors, 17*, 325-345.

Velicer, W. F., & Colby, S. M. (2005a). A comparison of missing data procedures for ARIMA time series analysis. *Educational and Psychological Measurement, 65*, 596-615.

Velicer, W. F., & Colby, S. M. (2005b). Missing data and the general transformation approach to time series analysis. In A. Maydeu-Olivares & J. J. McArdle (Eds.), *Contemporary Psychometrics. A Festschrift to Roderick P. McDonald* (pp. 509-535). Hillsdale, NJ: Erlbaum.

Velicer, W., & Fava, J. (2003). Time series analysis. In J. Schinka & W. Velicer (Eds.), *Research Methods in Psychology* (pp. 581-606). Vol. 2 of *Handbook of Psychology*. New York: Wiley.