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Agenda

Tuesday, May 18, 2010
Stewart Center, Room 218

7:30 a.m.  Registration, Coffee hour
8:30 a.m.  Welcoming Remarks

   Dr. Dennis Savaiano, Dean, College of Consumer and Family Sciences
   Dr. Shelley MacDermid Wadsworth, Director, Center for Families

9:00 a.m.  Introduction to Dyad Data Analysis

Richard Gonzalez, PhD, University of Michigan

South Ballroom, Purdue Memorial Union
10:30 a.m.  Poster Session: “Family Influences on Health Behaviors and Health Outcomes”
12:00 p.m.  Lunch (provided for registrants)

Stewart Center, Room 218
1:30 p.m.  Research Methods for Studying Families

   Alan Acock, PhD, Oregon State University

2:30 p.m.  Design and Analysis of Daily Diaries

   Niall Bolger, PhD, Columbia University

3:30 p.m.  Coffee break
4:00 p.m.  Panel Discussion
5:00 p.m.  Wrap-up

Wednesday, May 19, 2010
Stewart Center, Room 218
8:00 a.m.  Coffee Hour
9:00 a.m.  Concurrent Workshops (pre-registration required)

   Topic B:  Analysis of Diary Data from Dyads, Niall Bolger
   Topic C:  Intergenerational Family Research Methods, Alan Acock

12:00 p.m.  Conference concludes
Keynote Speakers’ Biographies

**Dyad Data Analysis**

Richard Gonzalez, PhD, is a Professor in the Departments of Psychology, Marketing and Statistics at the University of Michigan. He is a fellow of the American Psychological Association and the Association for Psychological Science. His research focuses on decision-making processes, including medical decision-making, and is funded by the National Science Foundation. He is a leading authority on dyadic data analysis, with publications that develop and describe cutting edge methodologies for dyad data analysis, and papers using dyadic methods in research on families and health. Additionally, he has served as associate editor for the *American Psychologist* and *Theory and Decision*.

**Family Research Methods**

Alan Acock, PhD, is the Distinguished Professor of Family Sciences and the Barbara Knudson Endowed Chair of Family Policy in the Department of Human Development and Family Studies at Oregon State University. His program of research is focused on intergenerational family processes that influence the well being of family members. He was selected by the National Council on Family Relations (NCFR) to serve as a co-editor on their *Sourcebook of Family Theory and Research*. In addition, he is the lead author for the chapter “Contemporary and Emerging Research Methods in Studying Families” in this NCFR Sourcebook, among many methodological contributions to family research methods.

**Analysis of Diary Data from Dyads**

Niall Bolger, PhD, is a Professor of Psychology at Columbia University. His research program is focused on dyad members’ responses to their own and to one another’s experiences of stress. He studies adjustment processes in close relationships using intensive longitudinal diary studies and lab-based studies of dyadic behavior, emotion, and physiology. He is a preeminent scholar in the design of daily diary methods to capture “life as it is lived,” and techniques to analyze change processes in individuals and couples. He applies his methodological developments in his studies of interpersonal processes and psychological and relational well being of couples under stress. Additionally, he has served as associate editor of the *Journal of Personality and Social Psychology: Interpersonal Relations and Group Processes*.
Keynote Presentation

Family Variables: Latent Class and Latent Transition Analysis

Alan C. Acock

Most studies of family life involve studying individual family members or pairs of family members. What is the effect of divorce on child outcomes? How much does mother’s education influence child outcomes? What happens to the development of mother-child conflict during adolescence? In each of these, the typical unit of analysis is the individual although advances in dyadic analysis make it possible for the dyad to be the unit of analysis. By contrast, there is a relative dearth of research where the family is the unit of analysis. What happens to family enmeshment when a second child enters the family? What happens to family conflict when the oldest child enters adolescence? Are there clusters of families that are differentiated on religiosity? Are these clusters stable after the birth of the first child? We can consider individual level variables either as a cause of family characteristics or as consequences of family characteristics. Does an only child who is female result in different patterns of family interaction than an only child who is male? In this question the individual characteristic, i.e., the gender of the only child is the independent variable and the family characteristics on interaction patterns is the dependent or outcome variable. Alternatively, we could have the family level variable be the independent variable and an individual level variable be the outcome. For example, does the interaction pattern that characterizes a family influence child well-being. Beyond this we could have relationships between two or more subsystem family variables such as the relationship between the style of conflict resolution of the parents and the style of conflict resolution of sibling children.

To analyze families as the unit of analysis we need to re-think what we are doing. Most individual level analysis had been what is labeled variable centered. We are interested in how one or a set of individual level variables are related to one or a set of other individual level variables. This is illustrated above by the relationship between

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mother’s education and child outcomes. A distinguishable way of approaching analysis is labeled person-centered. Here the question is whether there are groups of people who cluster together. Examples of person-centered research include k-cluster analysis, latent class analysis, and latent profile analysis. For example the Muthén’s did a study of alcohol usage of young adults from the teens to the 30s. They found three distinct clusters of people. One group had a low usage of alcohol from their teens to their 30s. The second group had a dramatic increase from their teens to their early 20s, but then dropped of to a moderate level by their 30s. The third group mimicked the second group up to about 22, but then did not have any drop-off in their drinking behavior. Each of these three groups were homogeneous within their group, but heterogeneous between groups. The Muthén’s method of analysis was to estimate a growth curve, but then extend this using a mixture model to find clusters that had clearly differentiated growth curves.

The idea of a mixture model is important to understand and the failure of most traditional researchers to look for mixture models reflects a fairly naïve assumption about the distribution of people on many variables. A single variable can be used to clarify what a mixture model is doing. When we look at the distribution of a variable, it may appear to be normally distributed for the entire sample. However, there may be two distinct groups, one with low scores and one with high scores. For example, we might consider a persons pleasure watching professional football games. Many more husbands find this pleasurable than do their wives. We might imagine there are two groups. The first consists mostly of women along with a few men and they tend to dislike watching professional football games. The second group consists mostly of men along with a few women and they tend to like watching professional football games. The composite population is a mixture of two distinctly different populations. It is important to recognize that this applies to more than attitudes toward watching professional football games. When people write about “his” marriage and “her” marriage, they are asserting that there are two distinguishable distributions on key dimensions of family life. They may report different means for wives and husbands. A mixture model goes beyond comparing means to identifying different distributions. A mixture model is illustrated in Figure 1. What appears to be a single distribution (solid curve) is actually made of two distinct groups (dashed curves), one with
low scores and the other with high scores. There is very little overlap between these to distributions.

![Figure 1 — A mixture model](image)

Family research can extend person-centered mixture models to have the family be the unit of analysis. We can use this to identify clusters of families that are homogeneous on one or more variables, but clearly differentiated from other clusters of families. In doing this we utilize a set of variables about family members (wife’s view, husband’s view, child’s view of a variable) or family characteristics (income, family size, length of marriage, age at first birth, race/ethnicity, geographic location) to identify clusters of families, much like the Muthén’s identified different clusters of individuals. The variables we use to identify the clusters could be binary (yes/no) in which case it is often called latent class analysis or continuous in which case it is often called latent profile analysis, or a combination of binary and continuous variables. Increasingly, the term latent class analysis is used regardless of the measurement level of the variables and this is the label we will use for the rest of this presentation.
Figure 2 illustrates a latent class analysis. The Classes (groupings) are represented by C in an oval. If we had three classes we might label them C#1, C#2, and C#3 (read class number 1, etc.). There are $k$ variables, $y_1, y_2, \ldots, y_k$, used to identify the classes. The score of the individual or family on each of the $k$ observed variables depends on their class membership. In latent class analysis each person or family will have a probability of being in each class. Notice in Figure 1 that although there is clear separation, there is still some overlap. If the Gonzales' have a probability of 0.8 of being in C#1, 0.1 of being in C#2, and 0.1 of being in C#3, we would place them in the first class. This is fundamentally not a deterministic classification, but a probabilistic classification. If the latent class analysis is able to identify distinct classes, then the probabilities associate with each class will be that those for the Gonzales'. If, however, the latent class analysis is not able to identify distinct classes the probabilities might be 0.40, 0.35, and 0.25 where there is no clear classification choice.

Latent transition analysis of family variables—Alan C. Acock

Figure 2—Latent Class Analysis
At the bottom of Figure 2 is one way of describing the results where we have three classes. In Figure 2, a diamond is used for the class that is high on every variable, a downward pointing arrow is used for the class that is very low on most of the variables, and an arrow pointing to the right is used for a generally middle level class. The diamonds, and arrows are the means (if the variable is continuous) or the probability of endorsing the item (if the variable is binary) of the members of each class. Notice that the middle class is actually lowest on variable $y_6$. Also, the middle class is fairly close to the highest class on the first four variables, but it is fairly close to the lowest class on the last three variables. A clinician counseling people in the middle class would likely want to focus on whatever family characteristics were represented by $y_5 - y_7$, they would be especially focused on $y_6$, and be less concerned about whatever family characteristics were represented by $y_1 - y_4$.

Class membership can be important in a number of ways. We might want to explain why some families are in one class and other families are in a different class. Does age at marriage or religiosity predict whether a family will be in the class that has strong or weak family interaction patterns? Correspondingly, we may use the class a family is in to explain a distal outcome variable. Does a family that has strong family interaction patterns have children who become better parents? Figure 3 illustrates how we can add explanatory variables and distal outcomes to our latent class analysis.

![Figure 3—Explanatory variables and distal outcomes combined with a latent class analysis](image)

In Figure 3, the box containing $x_i$ is a vector of explanatory variables. It could be as simple as the age at marriage, or it could have multiple variables and even direct and indirect effects. The box containing $y_i$ is a vector of distal outcomes. Again, this could be a
single outcome or a set of outcome variables. As you can imagine, these extensions of latent class analysis can be as complex as is appropriate to the research question. Regardless of the research question, however, these analyses have the family level variable, C, as the unit of analysis.

This in itself is an exciting extension on traditional research methods for studying families. However, this can be further extended to longitudinal models. In longitudinal models we have data on a set of families that is repeated over time. We might have indicators of family interaction patterns measures when the oldest child is 10, again with the oldest child is 15, and a third time when the oldest child is 20. With longitudinal data our focus on is change.

Two of the methods for analyzing longitudinal data are to estimate a growth curve or to do what economists refer to as an auto-regressive model (sometimes called Markov modeling). Applications of growth curves are increasingly common in family studies, but auto-regressive models, especially when combined with latent class analysis are not. The focus of this presentation is on auto-regressive models that are built onto a latent class analysis. When auto-regression modeling and latent class analysis are combined the most common label is latent transition analysis. Both a latent growth curve and a latent transition analysis are illustrated in Figure 4.

(continues on next page)
Figure 4—A growth curve model and latent transition analysis

The top illustration in Figure 4 presents a simple growth curve. We have variables measured at three time points. This is the minimum for a simple linear growth curve although four or more points is greatly preferred for a linear model to facilitate more meaningful tests. Typically, a growth curve imposes a particular functional form on the growth process such as that it is linear or quadratic. A linear growth curve is especially restrictive since it assumes a constant rate of growth and many developmental processes have periods of rapid growth and other periods of dormancy. A quadratic form allows for some flexibility, but is still unable to fit a process that does not conform to this functional rule. The imposition of a functional form is not necessary, since only two points need to be fixed making it possible to estimate the mean at each time point instead of imposing a particular functional rule. Imposing a particular functional rule, the goal of the growth model is to identify the intercept growth factor and the slope growth factor where the intercept reflects the starting point (depending on where the time variable was centered) and the slope reflects the rate of growth in the process.

The illustration on the bottom of Figure 4 represents a latent transition analysis. The $C_1$, $C_2$, and $C_3$ are three latent class variables estimated at three time points, for instance when the oldest child is 10, 15, and 20, respectively. The $y_{ij}$ are indicators of the
family variable being measured. The subscript $i$ refers to the observed variable where $i = 1, 2, 3, \ldots k$, and the subscript $j$ refers to the wave where $j = 1, 2, 3, \ldots m$. If the family variable involves the quality of the family interaction pattern, $y_{1j}$ could be the mother’s report, $y_{2j}$ the father’s report, $y_{3j}$ the oldest child’s report, $y_{4j}$ an observers report, and $y_{5j}$ a score of the family on a 15 minute discussion of some relevant issue. Alternatively, each $y_{ij}$ might represent a different aspect of family interaction such as support, control, tension, and commitment.

The number of distinct classes at each wave, $C_{1#1}, C_{1#2}, \ldots C_{1#n}$ may be the same at each wave $j$ or may vary across waves. For example, when the oldest child is 10, there might be just two classes, $C_{1#1}$ and $C_{1#2}$, the first consisting of families that have very high quality interaction patterns and the second of families that are challenged in terms of how they interact with one another. At wave two there may three or more classes reflecting the differential ability of different families to adjust to the complexities of having their oldest child in the middle of adolescence. At wave three there may again be just two classes. Alternatively, there may be consistency in the number of classes across the three waves. Beside the number of classes varying or not, the composition of the classes may be stable or not. Some families may be in the highest quality class at all waves, some in the lowest, some may move from the highest to the lowest and some may move from the lowest to the highest.

The solid lines going from $C_1$ to $C_2$ and from $C_2$ to $C_3$ are called first order auto-regressive coefficients. These coefficients estimate how stable or unstable the class membership of families is over time as it depends on the class membership at the previous time point. The dashed line going from $C_1$ to $C_3$ is called a second order auto-regressive coefficient. There may be some situations were with a lag of two there is still a direct influence. With an first order auto-regressive latent transition model the association would weaken over time, that is, the classification at wave 2 would be more similar to at wave 1 than would the classification at wave 3 (as in what is often called a simplex model).

In introducing latent class analysis we noted that there could be a vector of exogenous variables, $x_i$ that predict class membership and a vector of distal variables, $y_i$,
that are predicted by class membership. The top illustration in Figure 5 presents how this would be applied to a latent transition analysis in the case of an exogenous predictor of class membership. We could think of many exogenous variables that could influence the class membership of families at both waves. As an example, having a child who has Down syndrome might pose an extra challenge to the pattern of family interaction and this would be true at both waves.

Another extension of latent transition analysis that would be highly appropriate to analyzing family data is known as the mover-stayer model. This model can identify a latent class moderator variable, C. In this model, illustrated in the bottom of Figure 5, we posit an additional class variable, C, that has two subclasses, C#1, consisting of those families who stay in the same class and C#2 consisting of those families who move between classes. In this illustration the mover-stayer class, C., directly influences class membership at both waves, but also moderates the auto regressive linkage between the two waves, C₁ to C₂, as illustrated by the dashed line.

Figure 5—An exogenous predictor and a mover-stayer latent transition model

This has been an introduction to what I will present at the Purdue workshop. I will add a detailed worked example of these models showing how to use the Mplus program to
do this type of analysis with family data. I will post a complete document for the workshop at a web page, oregonstate.edu/~acock/lta around May 15th. Background readings are available there at this time. This document will extend this introduction to latent transition analysis and illustrate how to estimate selected models.

For those not familiar with the Mplus program, it is arguably the most advanced SEM package and the one that is most rapidly introducing new classes of models that are relevant to family studies. Mplus is extremely simple to program for many applications such as exploratory factor analysis, confirmatory factor analysis, structural equation modeling, and latent growth curves. It is also easily applied to complex (non-random) sample designs. It offers the most sophisticated treatment of missing values and that is easy to implement. The extension of Mplus to multilevel analysis is extraordinarily powerful, but is more confusing to program. The application to mixture models, of which latent transition analysis is one example, adds additional complexity to the programming. Because of this programming complexity, a detailed worked through example that explains the programming and the interpretation of the results should be very useful to anybody doing their first latent transition analysis of family data.

References

These references are available for download at www.statmodel.com or oregonstate.edu/~acock/lta


Additional Recommended Reading*:


*Articles by Niall Bolger can be accessed at: [http://www.columbia.edu/~nb2229/publications.html](http://www.columbia.edu/~nb2229/publications.html)*

These references are available for download at [www.statmodel.com](http://www.statmodel.com) or [oregonstate.edu/~acock/ltam](http://oregonstate.edu/~acock/ltam)


Poster Session

Title
Beliefs about Spouses’ Role in Health Management and Reactions to Spousal Involvement among Individuals with Type 2 Diabetes

Authors
Rachel C. Hemphill, Mary Ann Parris Stephens, Karen S. Rook, Melissa M. Franks, & James K. Salem

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Abstract
Individuals experiencing chronic illness often receive assistance with disease management in the form of social support and control from the spouse. In some cases, however, spousal involvement may violate patients’ beliefs about the role spouses should play in health management. This study of elderly individuals with type 2 diabetes and their spouses (N= 120 couples) investigated whether patients’ beliefs about spousal involvement moderated the relationship between spouses’ support and control and patients’ reactions to spousal involvement in diabetes management. Among patients with low prescribed spousal involvement, spouses’ support and control were positively related to patients’ resistance.
Poster Session

Title
The Role of Equitable and Equal Support Exchange in Parent-Adult Child Relations

Authors
Abigail R. Howard, J. Jill Suitor, and Karl Pillemer

Abstract
Classic theories of social exchange suggest that relationships are more harmonious when both members of dyads believe that their exchanges are fair. However, the level and frequency of exchange, rather than perceptions of fairness, have been the focus of this research. Using reports from 431 mothers regarding each of their adult children, we explore whether perceptions of relational equity are better predictors of closeness and conflict than are mothers’ reports of actual exchanges of emotional and instrumental support. Mixed model analyses revealed that mothers’ perceptions of equity were more consistent predictors of relationship quality than were their reports of support exchanges.
Poster Session

Title
Communication and Diabetes Management Study

Authors
Rebecca Nichols, Casey Coker, Amber Seidel

Abstract
The primary purpose of this study is to learn how patients and spouses communicate with their healthcare providers when both attend a medical visit together. This study requires the participation of both marital partners. Participants are asked to complete two self-administered questionnaires 30 minutes prior to your scheduled visit with their healthcare provider, have their scheduled visit audio-recorded, and fill out follow-up questionnaires one month later. We are currently recruiting participants and collecting data.
Poster Session

Title
Role of Spouses’ Diabetes-Related Anxiety in Their Involvement in Diabetes Management

Authors
Cynthia M. Khan, M.A., Kent State University
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Mary Ann Parris Stephens, Ph.D., Kent State University
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James K. Salem, M.D., Summa Health System

Abstract
In a 7-day, diary study of adults with diabetes and their spouses (N = 70 couples), spouses’ diabetes-related anxiety was investigated as a moderator of the associations between either patients’ diabetes-related anxiety or dietary adherence and the spouse’s provision of either diet-related support or control. A stronger, positive association between patients’ dietary adherence and spouses’ support provision was found when spouses were less anxious than when they were more anxious. No moderation was found for spouses’ control. However, spouses’ anxiety was associated with more support and control provision. Findings suggest that spouses’ anxiety can promote their involvement in diabetes management.
**Title**
Role and Gender Differences in Diet-Related Support Exchanges of Patients with Diabetes and their Spouses

**Authors**
Emily L. Smith, B.S.; Melissa M. Franks, PhD; Amber J. Seidel, M.A.; TusaRebecca E. Schap, MSc, RD; Carol J. Boushey, PhD, MPH, RD
Purdue University

**Abstract**
For many individuals, their support systems are activated during times of stress throughout all stages of life. The marital relationship is an important bond and spouses often offer support to one another to manage stressors in life. Individuals define what it means to be supportive in different ways and this difference in view can influence how support is provided and how it is received. Role and gender differences in diet-related support exchanges were investigated in couples in which one member of the dyad had type 2 diabetes. All patients in the marital dyads (N = 5 dyads) reported both receiving diet-related support from and providing diet-related support to their spouses. Likewise, most spouses of patients reported both receiving and providing diet-related support. Tests of mean difference revealed no significant differences in exchanges of diet-related support reported by patients and those reported by spouses (i.e., role differences). Likewise, no significant mean differences were detected between male and female patients in reports of exchanges of diet-related support or between patients’ female and male partners. Findings suggest that diet-related support is not just received by the patient and provided by the spouse, but both patient and spouse receive and provide diet-related support. Implications from this study suggest that diabetes education should include not only the patient but also the spouse who is likely to be involved with patients’ dietary management.
Poster Session

Title
Family and Environmental Influences on Obesity Among Latino Children

Authors
Joel E. Williams, MPH, Ph.D., Clemson University, Department of Public Health Sciences, Clemson Cooperative Extension Service

Abstract
Large numbers of Latinos have migrated to U.S. communities where they were sparsely present just a decade ago. These “new settlement” areas in the South are less adequately prepared to serve the physical and mental health needs of Spanish-speaking immigrants. Latinos have the highest rates of overweight and obesity and Latino children face a greater risk for developing chronic diseases compared to their non-Hispanic White counterparts. Multiple environmental and family contextual factors influence weight status among children. Relationships among these factors are complex and not well understood. Acculturative stress adds an additional layer of influence with culturally-specific consequences for immigrants.
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