Family-Based Prevention in Developmental Perspective: Design, Measurement, and Analytic Issues

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In recognition of the potentially critical role the family plays in substance use, the National Institute on Drug Abuse (NIDA) is expanding its school-based prevention efforts to include the family. For the developmentalist, this new focus raises challenging methodological issues. These issues largely reflect paradigmatic interests in change and multilevel systems, themes that are common to numerous developmental approaches: ecological (Bronfenbrenner 1979), contextual (Lerner and Kaufman 1985), interactive (Magnusson 1988), individual-socioecological (Valsiner 1987), and the lifecourse (Elder and O'Rand 1995).

Since World War II, American family life has changed enormously. Demographers observe greater variability in the age at which marriages form, a decrease in fertility, and increases in marital dissolution; blended families; and alternatives to married living, including cohabitation and single-parent households (Cherlin 1988; Goldscheider and Waite 1991). Social theorists maintain that the family has changed from a constellation of socially defined roles to a primary group of individuals who negotiate their responsibilities and expectations, a pattern often seen in dual-earner families (e.g., Giddens 1992). Thus, researchers must be sensitive to the appreciable diversity that distinguishes contemporary "families," as well as how the family changes according to several different temporal frames implicating history, the stages of family life, and the life-histories of individual family members. What are the design, measurement, and analytic strategies that facilitate the study of these temporal complexities?

The study of the family is also complicated by its multilevel nature. Families are located within communities and neighborhoods having characteristics that are potentially relevant to the adaptive patterns of youth. These variables include job opportunities and the availability of social services (Furstenberg and Hughes, in press), the extent to which others assume responsibilities for monitoring children (Fletcher et al. 1995), and social disorganization as reflected in such factors as crime, mobility, and the concentration of poverty (Sampson 1992). At the same time, individuals are located within families that have unique characteristics, including, for example, cohesion and the experience of negative family events. What is the relative importance of community, family, and individual-based variables and the interactions among them?

This chapter presents a concise overview of methodological issues confronting developmentalists interested in the study of drug abuse prevention in families. Issues of design, measurement, and analysis in the study of family prevention programs are considered, with special emphasis on the testing of dynamic and multilevel hypotheses.

DYNAMIC ASPECTS OF FAMILY PREVENTION RESEARCH

Family prevention research examines patterns involving substance use, family structure and relationships, psychosocial factors, and context— constellations of variables that are potentially dynamic (i.e., they are subject to change in systematic ways over time). Many of the methodological issues raised by the study of these phenomena stem from the use of longitudinal data. After a brief conceptual overview of some dynamic variables in family-based prevention, the authors discuss (1) prominent design issues including how families are sampled, missing data problems, and the number, timing, and spacing of observations; (2) measurement issues, including validity, factoral invariance, and reliability in longitudinal designs; and (3) statistical methods that are particularly valuable when studying longitudinal data, including latent growth-curve models, survival analysis, and latent transition analysis.

Dynamic Variables in Family-Based Prevention

Substance Use and Related Psychosocial Variables. Substance use and many closely related psychosocial variables figure prominently in prevention research. The use of individual substances changes across the lifecourse, as individuals start out as nonusers, experiment with a substance, and then in most cases develop a pattern of use, which may be abstinence, occasional use, more regular use, or dependence. Substance use onset may be thought of as a stage sequence made up of experiences with individual substances (Collins et al. 1994; Kandel and Yamaguchi 1985). For example, Collins and colleagues (1994) characterized the early-onset process as a sequence consisting of trying alcohol, trying tobacco, and having a first experience with drunkenness before moving on to low-level advanced use.

Dynamic psychosocial influences on substance use may exert effects at any point in the lifecourse. Perceptions of peer use, normative beliefs, attitudes toward risk-taking, poor relationship with parents, and feelings of rebelliousness are all dynamic influences on substance use onset (Hawkins et al. 1992). Substance use in adults may fluctuate in response to external influences, such as work-related stress. Increased use of alcohol or prescription drugs by an elderly family member may stem from growing depression associated with a disability or the discomfort of a lengthy illness.

Family Structure: Role Set and Membership. In the late 1980s it was observed that roughly two of three marriages would end in dissolution (Martin and Bumpass 1989). Hofferth (1989) estimated that one-third of children born in the 1980s will still be living with both natural parents by age 14, while one-fourth will be living with a natural parent and a stepparent. These estimates suggested that about one-half of all children living with two parents will have one parent who is a late arrival. Furthermore, a plurality of children (exceeding 40 percent) will be in a single-parent household, most frequently with the mother. In short, a large percentage of American youth will live in a variety of intact and nonintact family types (Wojtkiewicz 1992).

Consider a hypothetical case consistent with these demographic trends: a household consisting of a wife, husband, and one son agrees to participate in a 5-year longitudinal study. At some point in the course of the study, the parents divorce and each remarries, with the son in joint custody. The mother now reports her family as her son and her new husband. The father now reports his family as his new wife, her two children from a previous marriage, and his son. The son began with a mother and father, but as the study comes to a close only 5 years later, he has a natural mother and father, a stepmother and stepfather, and two stepsiblings. Further complexity is likely if the study includes a substantial number of older adolescents. For example, the son may cohabitate with a companion or live in an institutionalized setting such as a dormitory.

Given the simplest case of family structure and membership—a family that remains intact through the course of a study—issues of the family cycle may still add considerable complication (Elder, in press). Family cycle typically refers to the ordering and timing of stages traditionally associated with family life: courtship, engagement, marriage, first birth, the spacing of children, the departure of children from the home, and death of a spouse (Hill 1970). Many of these elements have uncoupled in sequence and timing in the past several decades (Cherlin 1993), creating great diversity in what constitutes "family life."

Context. Sociologists conceptualize the family as a set of relationships linking the individual with a changing society (Elder and O'Rand 1995; Furstenberg 1985). First, relatively discrete events such as wars and economic downturns can affect family life. For example, Elder's (1974) studies of the Great Depression demonstrate that economic decline frequently leads to marital tensions, poor parenting, and changes in children's psychological well-being, problem behaviors, and health-related behaviors. Studies of household income suggest that an appreciable number of families move in and out of poverty on a yearly or even monthly basis (Bane and Ellwood 1986; Ruggles and Williams 1989). Families may also experience an abrupt change in context because of geographic mobility. Roughly 18 percent of 15- to 19-year-olds experienced a move in a 1-year period beginning in 1990 (U.S. Bureau of the Census 1992). Long-term change may also have an impact on family life; changes such as economic restructuring, outmigration, and the reorganization of rural communities are relatively nondiscrete events that have dramatically transformed relationships within the family (Elder et al. 1993).

Design Considerations When Dynamic Variables Are Involved

In a series of articles on design for developmental research, Schaie (1965, 1973) and Schaie and Baltes (1975) point out that there are three broad classes of predictors of intraindividual change over time: age, cohort, and time. Age refers to the individual's chronological age at each observation; cohort refers to the birth cohort or generation to which an individual belongs; and time refers to the date that an observation is made on an individual. These are not independent, since any two of them determine the third. For example, an individual who is 65 years old (age) in 1995 (time) can belong to only the 1930 birth cohort, which means that this individual's development has been influenced by factors such as the Great Depression and World War II. The age-cohort-time distinction is particularly useful for highlighting the strengths and weaknesses of the two major design possibilities: cross-sectional and longitudinal.

In a cross-sectional design, all data are collected at a single time for all participants. If the primary focus of a study is group comparisons at one point in time, a cross-sectional design should probably be used. However, cross-sectional results may be misleading when individuals of different ages are compared. For example, a researcher may be interested in how attitudes toward substance use differ between generations. Suppose it is found that children have more permissive attitudes toward drug use when compared with their parents. It may be tempting to infer a developmental trend of decreasing permissiveness with age (i.e., parents have less permissive attitudes toward drugs because older people are less permissive than younger people). However, the cross-sectional approach confounds age and cohort: All of the individuals who are a particular age belong to a particular cohort. Thus, an alternative explanation is that the observed differences are due to cohort membership: Perhaps children are exposed to a more permissive culture today when compared with their parents' formative years. According to this explanation, as these children age, they will not become more permissive.

The ability to disentangle the age-cohort confound is one benefit to longitudinal designs. In the longitudinal approach, data are collected on individuals repeatedly across time. Longitudinal studies are more expensive and time consuming, but unlike cross-sectional studies, they offer the ability to observe intraindividual growth over time directly. One problem with traditional longitudinal designs is that only a single cohort is studied, making it impossible to determine whether the results will hold for another cohort. To address this problem, Schaie (1965) suggested the cohort-sequential design, a longitudinal study involving several cohorts simultaneously. Table 1 illustrates the pattern of data collection in a cohort-sequential design. Children were measured yearly beginning in the seventh grade. Each year for 4 years a new cohort of seventh graders is added to the study. Any analyses examining change over time in cohort 1 can be replicated in the other three cohorts. Cohort-sequential designs similar to this have been used extensively in drug abuse prevention research (e.g., Graham et al. 1990; Hansen and Graham 1991).

Sampling. The sampling of families for substance use prevention research requires a clear operational definition of the family, especially given the potentially dynamic nature of family structure and membership. In fact, the rapidity with which family composition can change presents a challenge to those formulating a sampling plan for family-based prevention studies. One operational approach is to limit

TABLE 1. *Cohort-sequential design.*

Cohort Number	Year 1	Year 2	Year 3	Year 4	Year 5
Cohort 1	Grade 7	Grade 8	Grade 9	Grade 10	Grade 11
Cohort 2		Grade 7	Grade 8	Grade 9	Grade 10
Cohort 3			Grade 7	Grade 8	Grade 9
Cohort 4				Grade 7	Grade 8

the sample to those families meeting certain characteristics (e.g., restrict the sample to intact families in which the parents have been married at least 5 years). This will not eliminate the problem, but it has certain advantages. First, by requiring that the parents be married at least 5 years, the researcher is ensuring that the marriage has endured past a period of high risk for divorce. Second, this plan ensures a baseline observation where all families are roughly comparable. Third, a more homogeneous sample tends to reduce unexplained variance (Hansen and Collins 1994), potentially increasing statistical power.

However, this approach also has some significant disadvantages. The likelihood of divorce, remarriage, and remixing of families is reduced but by no means eliminated by this strategy. Furthermore, the study's generalizability is severely reduced, because the conclusions describe only intact families. In family-based research, as in most other areas in the social sciences, the researcher is often confronted with a painful tradeoff. Limiting sampling eligibility reduces unexplained variance, potentially increasing statistical power and internal validity. However, limitations of sampling eligibility reduce external validity (Hansen and Collins 1994). This is a difficult decision, with the choice highly dependent on the precise circumstances of a project. The authors' bias favors maximizing internal validity, because a study with sufficient internal validity at least provides a basis on which to plan further research involving a more heterogeneous sample. In contrast, a study with poor internal validity does not allow for conclusions about any population.

Missing Data and Subject Attrition. Both cross-sectional and longitudinal research are subject to problems caused by missing data. Data can be missing because study participants fail to complete one or more items on a questionnaire or because participants were unavailable for one or more waves of data in a longitudinal study. In fact, one of the most serious difficulties of longitudinal research is the virtual impossibility of conducting a study over a period of years without some subject dropout, often referred to as attrition. If attrition is truly random (i.e., every subject in the study has an equal probability of dropping out), then the only problem is the loss of statistical power associated with a reduced sample size.

Although in most studies a proportion of subject dropout can be considered random, a substantial amount of subject dropout is commonly nonrandom. Nonrandom attrition can affect both the internal and external validity of a study. Attrition affects internal validity if it occurs differentially between treatment and control groups. A classic example of differential attrition occurs when an intervention is administered, such as a family-based drug abuse prevention program. The most dysfunctional families may drop out of the program, or at least make themselves unavailable for data collection. This leaves a higher proportion of well-functioning families in the treatment condition, which can make the treatment condition look more effective. External validity may also be affected. For example, lower socioeconomic status (SES) families tend to be more transient and therefore to move out of the school district and the study. The loss of these families means that the generalizability of the study to lower SES groups is limited.

Attrition is more complicated when families are the focus of study. An entire family can drop out of a study, or one or more members of a family can drop out. Divorce can mean that over the course of a longitudinal study some family members are no longer available. A complicated situation also arises when a family member is "replaced," as when a remarriage places a stepparent in the home. The researcher then must decide how to treat this newly configured data—treat the father's data as missing after the divorce and add the stepfather's data, treat the stepfather's data as father's data, or attempt to collect data on the father and stepfather. These issues must be thought through, keeping in mind the questions a particular study is designed to address.

It is important to minimize the amount of missing data due to nonresponse, subjects not making themselves available for a particular data collection session, or subjects leaving a study entirely. In family-based research, as in all research, subjects should be given enough time to complete any measurement instruments or interviews and should be strongly encouraged not to skip items. Family research may require more time for this than school-based research when there is variability in the ages and reading skills of people completing the instruments.

It is also important to set aside resources for the purpose of minimizing the amount of missing data. In family-based research, more resources are needed for this purpose than for school-based research. Families do not appear for data collection in large groups at previously scheduled times, the way children in school are available for data collection in class. Instead, repeated attempts must be made to schedule data collection sessions with families, at times and in locations that are convenient for them. In many cases not all family members will be home for a data collection visit, making more than one visit necessary.

In longitudinal family-based studies, resources should be devoted to finding and collecting data from those who drop out of a study. Good planning can make this more efficient; for example, on the first data collection occasion, information can be obtained to make it easier to track people if they move, such as place of employment, driver's license number, or the address and phone number of a close friend or relative. This strategy has become especially valuable with recent advances in corrections for missing data (Little and Rubin 1987; Schafer, in press). These advances provide a way to make use of all the data that are present and to eliminate much of the bias associated with nonrandom attrition. Using missing data procedures, the researcher can approximate the data had there been no subject dropout.

The conventional wisdom has been that researchers attempt to find every subject who has dropped out of a study, with a goal of achieving a completely restored dataset. In practice, some of these subjects will be relatively easy to find, others less so. Because every study has finite resources, usually the effort to contact dropouts must end before every dropout has been found. In fact, the result of this approach is usually a sample of dropouts who are relatively easy to find, while the type of subject who is difficult to find is underrepresented.

However, statistical procedures can most effectively estimate what the results would have been like with complete data if data from a random sample of dropouts were available (Graham et al. 1994). In other words, if missing data procedures are to be used, the goal of contacting dropout subjects should be to obtain a random sample of subjects who have left the study rather than to obtain a complete data set, given that obtaining a complete data set is unrealistic. This suggests a strategy where a random sample of dropouts is pursued vigorously until complete, even if this random sample is considerably smaller than what would have been obtained if attempts were made to contact all dropouts. Even when an exactly representative sample of dropouts is only approximated, this strategy is still preferable (Graham et al. 1994).

Number, Timing, and Temporal Spacing of Observations in a Longitudinal Study. In longitudinal research it is common to collect data in "waves" (i.e., to collect data at approximately the same points in time for all subjects). In family-based research, data might be collected on all subjects once each semester of the school year and once in the summer. When this data collection strategy is used, the study is often referred to as a "panel study." In other data collection strategies, data may be collected at different times for different individuals.

When designing a longitudinal study, it is important to pay careful attention to the number, timing, and temporal spacing of data collection. Every longitudinal study, except those in which only the simplest linear model is hypothesized, should involve more than two waves of data. A common problem in otherwise well-designed longitudinal studies is that too few data collection sessions, spaced too far apart, are planned. Then it becomes difficult or impossible to model growth accurately, because too much of the growth has occurred between observations. Consider the growth depicted in figure 1. Few would describe this growth as linear, yet it appears linear if measures are taken only at times 1, 7, and 13.

Careful planning is needed if data collection points are to optimize the view of individual growth; this planning should balance conceptual and methodological considerations, findings from previous research indicating plausible patterns of growth, and practical issues such as funding. During periods of rapid change, measurement should occur more frequently. A more slowly moving or strictly linear process can be measured with fewer observations spaced farther apart.

In most cases, researchers can formulate reasonable hypotheses about the pace and direction of change. For example, some periods of the lifecourse are characterized by a higher risk for the onset of particular substance use. Also, many individuals run a higher risk for substance use during

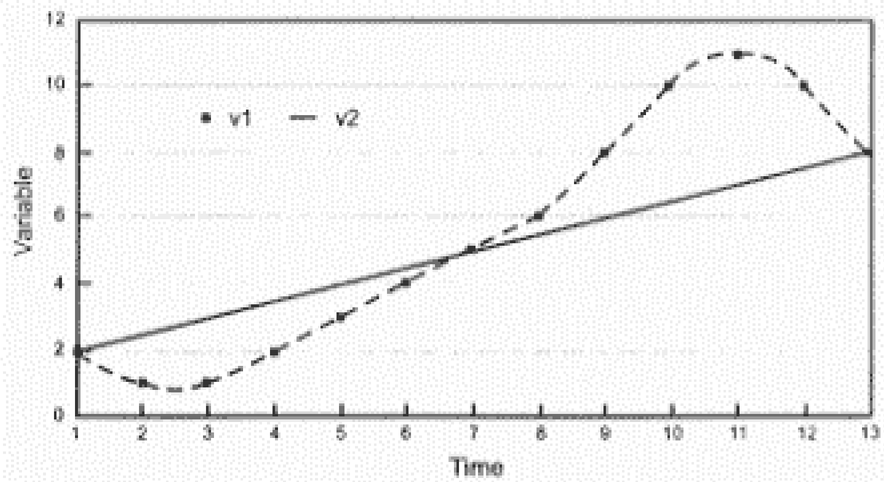

FIGURE 1. *The broken line represents change in a dynamic variable. The solid line represents how this growth would appear if measured only at times 1, 7, and 13.*

periods of change. Simmons and Blyth (1987) showed that adolescents experiencing multiple transitions simultaneously are at a higher risk for depressed mood. Thus, knowledge about the age distributions that describe such transitions as pubertal change, the transition to junior high school, and dating patterns may all serve to inform the "when and how many" of data collection.

Statistical considerations are also relevant to the timing and spacing of observations. Statistical procedures for modeling growth and change make different requirements about the spacing of observations in a longitudinal study. Some methods, such as repeated measures analysis of variance with polynomial contrasts, require that observations be evenly spaced and conducted at the same time for all individuals. Others, such as latent growth-curve modeling (Willett and Sayer 1994) and latent transition analysis (Collins and Wugalter 1992), require that observations take place at the same time for all individuals, but not that they be evenly spaced. Approaches based on hierarchical linear models (Bryk and Raudenbush 1992) allow variation in both spacing and timing of observations.

Finally, data collection is expensive, and a shortage of resources may limit how frequently measurement can take place. Sometimes a compromise can be reached where more indepth data collection is alternated with shorter, less expensive data collection sessions. However, if data are collected too frequently, test-retest bias or other measurement effects can result. A balance must be struck between measurement frequent enough to allow close observation of dynamic phenomena and infrequent enough to avoid measurement artifacts.

The Experiential Sampling Method (ESM) represents an alternative approach to the temporal spacing of observations (Csikszentmihalyi and Larson 1992; Larson and Csikszentmihalyi 1983). Typically, individuals provide systematic self-reports at random occasions during the waking hours of a normal week. Participants carry signal devices and respond to randomly programed pages. These self-reports may include responses to standard scales of affect, control, self-perceptions, and physical well-being, as well as brief, open-ended descriptions of the activity. This method emphasizes ecological validity and the interactions of context and intrapsychic processes in the flow of activity (Hormuth 1986). Data files created from sets of these reports then constitute a description of a sample of random daily experiences.

For example, Larson and his colleagues (1992) use the ESM to study the personal and situational correlates of alcohol and marijuana use. The sample of 75 Caucasian adolescents is based on a stratified procedure at a large suburban high school and includes a range of students in terms of gender, grade level, and social class. Students carried electronic pagers and were signaled at random within every 2-hour time period between 7:30 a.m. and 10:30 p.m. on weekdays and until 1:30 a.m. on Friday and Saturday nights. Participants filled out a self-report form with each signal; the response rate was 69 percent for 4,489 time samples. Nineteen adolescents reported 25 occasions of alcohol use and 19 occasions of marijuana use.

An analysis of the objective circumstances of usage reveals that alcohol is consumed on Friday and Saturday evenings with groups of four or more, while marijuana use occurs at all times during the week, usually with just one other person. An analysis of subjective states during usage generally reveals heightened positive moods for alcohol (e.g., feelings of happiness, sociability, and freedom), while use of marijuana is not strongly associated with positive changes in mood, though it is associated with a stronger motivation for usage. Larson and colleagues also used the ESM data to study one heavy marijuana user’s profile and reported that the individual used the drug to kill pain, cope with his family, and do homework, although usage was actually not related to positive changes in mood (see deVries 1992 for further applications and discussion of ESM). Sampling strategies such as this could prove valuable in developing prevention programs that are attuned to the daily experiences of users.

Measurement Issues in Family-Based Prevention Research

Cross-Sectional Comparisons Across the Lifecourse. Family-based research involves people from the entire lifecourse. Anyone from a newborn to a 100-year-old great-grandparent might be involved. This makes for very rich data, but it also presents significant measurement challenges. Before comparisons can be made across individuals at different points in the lifecourse, it is first necessary to establish that the measures to be used are equivalent so that a basis exists for the comparison. When one instrument is suitable for the entire lifecourse, procedures for establishing factorial invariance (Cunningham 1991; Horn 1991) can be used to provide evidence that the same latent variable is being measured by the instrument when it is applied to different age groups. However, factorial invariance procedures cannot be used when a variable must be operationalized differently for different ages. For example, there is evidence that temperament is an important factor in the development of substance use habits throughout the lifecourse (Tarter et al. 1990). However, temperament is manifested in very different ways at different points in the lifecourse. Suppose a study assesses temperament in infants by the amount of time spent crying, in younger children by rating characteristics of observed social interactions, and in adolescents through self-reports. To measure stability over time, or to examine intergenerational differences, the researcher must find a way to equate these three very different measures of temperament. Currently there is no well-established methodology for doing this.

Longitudinal Measurement of Dynamic Variables. The dynamic variables that appear so regularly in family-based substance use prevention research present special methodological challenges. In fact, the traditional approaches to instrument development that work well for many research settings fall short when used to develop instruments to measure dynamic variables. This largely has to do with how intraindividual variability, as opposed to interindividual variability, is treated. The traditional definition of reliability, an operational definition of measurement precision, is usually stated as the proportion of observed score variance in an instrument that is attributable to true score variance (Lord and Novick 1968). It is assumed that both true score and observed score variance are interindividual variances (i.e., variances between individuals at a single time). But when individual change over time is of interest (the individual can be an individual family as well), intraindividual variance, the variance in an individual's responses over time, becomes important.

Because the traditional definition of reliability does not involve intraindividual variance, it is not a definition of measurement precision for measures of dynamic latent variables. Furthermore, irrespective of the amount of intraindividual variability, if there is little or no interindividual variability, a measure is unreliable by the traditional definition. (This is one reason why it can be difficult to achieve high reliability for measures of substance use based on a sample of young children who are early in the onset process; under these conditions there is very little interindividual true score variability in substance use.) This means that procedures such as computing Chronbach's alpha do not help to determine the quality of a measure for a dynamic latent variable (Collins and Cliff 1990).

Several alternatives to traditional approaches have been suggested for developing measures of dynamic variables. Willett (1989) showed that traditional reliability theory can be extended to dynamic variables by incorporating a growth-curve model. However, this extended definition still relies on the presence of interindividual variability. Collins and Cliff (1990) and Collins and colleagues (1988) extended the Guttman scale to longitudinal data. This approach had the advantage of not relying on the presence of interindividual differences, but was suitable only for dichotomous data fitting a fairly strict Guttman model. Embretson (1991) extended latent trait models for use with longitudinal data. However, these models too are primarily for dichotomous data from ability or cognitive tests, rather than for the psychosocial variables likely to be of interest in family-based research.

Statistical Analysis in Dynamic Family-Based Prevention Research

Many of the research questions in family-based prevention are phrased in terms of intraindividual growth and change over time. For example, What is the hazard profile that describes the probability of substance use across the teen years? Is this profile different depending on whether adult family members are heavy substance users? Can an intervention alter its course, and if so, in what way? Does an intervention alter the probability of onset in an individual, or does it change the point at which probability of onset levels off? Until recently, it was difficult to answer these kinds of questions because statistical procedures for handling short-term longitudinal data did not exist. Today there are numerous statistical procedures that can address these kinds of questions, including latent growth-curve modeling, survival analysis, and latent transition analysis.

Growth-Curve Modeling. Latent growth-curve models depict repeated measures as intraindividual growth parameters and their interindividual differences (McArdle 1986; McArdle and Epstein 1987; Willett and

Sayer 1994). As opposed to multiwave autoregressive models, which estimate interindividual change between measurement occasions, latent growth-curve models estimate the full trajectory of change across an individual's measurement points. The growth-curve parameters estimated in a latent growth-curve framework allow for the testing of numerous developmentally sensitive hypotheses.

First, a simple model provides estimates of the average growth curve (intercept and slope) across individuals and the variances of these population parameters, which indicate the amount of interindividual variation in the growth parameters. For example, one could estimate a growth curve that describes the average number of cigarettes smoked per week in the past month over three measurement occasions. The intercept would indicate the average number of cigarettes smoked at a reference timepoint (e.g., the first occasion), while the slope would tell the direction and rate of change in the number of cigarettes smoked over the time period studied. A particularly interesting application of these trajectories involves testing whether prevention interventions affect developmental change: Growth curves can be estimated separately for two groups, one with a prevention intervention and a control group. The models' growth parameters can then be compared to ascertain whether the intervention had an impact on the level or rate of change in the criterion.

A second model provides estimates of how various factors predict differences between individual growth-curve parameters. Suppose there is significant variation in the slope parameter, indicating that individuals differ in the direction and/or rate of change in cigarette smoking. What factors explain why some individuals increase the number of cigarettes they smoke more rapidly than others? This question can begin to be answered by adding predictors of interindividual variability in the slope. For example, this approach was used by Bolger and colleagues (1995) to study the relationship between poverty and the developmental trajectories of children. A developmental trajectory of peer popularity was estimated, and family predictors were added to this model. The authors reported that children from families experiencing economic hardship had significantly lower levels of popularity among peers (i.e., hardship accounts for variation in the intercept of the popularity trajectory), although they enjoy an accelerated increase in popularity (i.e., hardship accounts for variation in the slope of the popularity trajectory) when compared with children from families without economic hardship.

Finally, latent growth models allow researchers to test hypotheses about interlocking trajectories between variables (i.e., whether variation in levels or rates of change in two variables are correlated) with associative or cross-domain models (Tisak and Meredith 1990; Willett and Sayer 1995). This class of hypotheses relates a growth parameter for one variable (e.g., rate of change in beer consumption) with a growth parameter in other variables (e.g., rate of change in parental monitoring) and so tests relationships between two developmental functions. For example, McLeod and Shanahan (in press) estimate growth trajectories of the family's cumulative years in poverty and the antisocial behavior of their children. They report that the slope describing cumulative years in poverty correlates significantly with the slope of children's antisocial behavior. Thus, rate of change in family experience is correlated with rate of change in children's psychosocial adjustment.

Survival Analysis. A slightly different type of question involves asking how long it takes for an event to occur: How long before a first experience with drunkenness? How much time between first trying a cigarette and onset of regular smoking? Does an intervention delay the first experience with marijuana? These kinds of questions can be addressed using survival analysis, which models time to an event (Singer and Willett 1994). Survival analysis is not a new approach, but it is relatively new to the field of prevention.

In their very helpful introduction to survival analysis, Singer and Willett (1994) illustrated the use of survival analysis to model relapse in ex-smokers. They used data collected monthly for 12 months beginning from when the smokers first quit. The survivor function describes the cumulative probability of not relapsing as a function of time. In other words, the survivor function represents the probability that a randomly selected individual has not relapsed by some particular time. The hazard function, which is a close relative of the survivor function, can be used to express the probability of relapse as a function of time. This differs from the survivor function in that it is not cumulative. Thus, it represents risk as a function of time. By examining the hazard function it is possible to identify points of time where risk is particularly high or low. Singer and Willett (1994) used a hazard function to show that the risk of relapse is highest in the first 2 months after a smoker quits smoking, declines in the third month, and increases again in the fourth month. This hazard function reveals risk periods when smoking cessation programs might want to concentrate efforts on preventing relapse.

Survival analyses have the capability of including both static and dynamic predictors in a model. In the smoking cessation example, it would be possible to add a static predictor that would allow the comparison of survival and hazard functions across several different types of cessation programs. It would also be possible to add perceived stress, also measured monthly, as a dynamic predictor of the risk of relapsing.

Latent Transition Analysis. It is often useful to think of substance use onset and related variables as stage sequences. For example, the early part of the substance use onset process can be thought of as a series beginning with alcohol or tobacco, then experiencing drunkenness for the first time, then going on to higher levels of use. This point of view can offer unique insights on the onset process. For example, Graham and colleagues (1991) showed that adolescents who initiated the onset process with tobacco were on an accelerated onset trajectory compared with those who initiated the onset process with alcohol.

Latent transition analysis (LTA) is a methodology for estimating and testing latent variable models involving stage sequences over time (see Collins and Wugalter 1992; Collins et al. 1994; and Collins et al., in press). LTA is analogous to covariance structure modeling in many ways. Like covariance structure models, LTA models provide parameter estimates that express the strength of the relationship between the manifest and latent variables. In covariance structure models, these parameters are factor loadings. In LTA models, a different parameter serves the same conceptual purpose. While covariance structure modeling involves a continuous latent variable and (usually) continuous indicators, LTA involves a discrete, stage-sequential latent variable with discrete, often dichotomous, indicators.

One of the most interesting aspects of LTA models is the transition probability matrix. This matrix expresses the probability of transitioning to a stage, conditional on earlier stage membership. For example, one element of the transition probability matrix would be the probability of transitioning to a stage involving drunkenness, given that the individual had tried alcohol in the immediately previous measurement occasion. An important advantage of the LTA approach is that the transition probability matrix is adjusted for measurement error, providing a clearer picture of stage transitions over time.

THE CONTEXT OF FAMILIES AND THE FAMILY AS CONTEXT: MULTILEVEL ISSUES

It has been recognized for some time that school-based research in substance use prevention is multilevel. For example, individuals are nested within classrooms, classrooms are nested within schools, schools are nested within school districts, etc. In multilevel data structures such as this, there are at least two sources of dependence among individuals. First, individuals within groups are not sampled independently. In most school-based prevention studies, classrooms or schools are sampled rather than individual subjects. Second, the treatment is delivered to groups rather than individuals, which means that group-level characteristics and dynamics have an effect on the outcome as well as individual-level characteristics of the subjects. These two factors can produce data that contain dependencies (i.e., an individual within a group tends to be more similar to other group members than to individuals outside the group). Most studies have found relatively little dependence among observations in the nested structures that occur in school-based studies (Graham et al. 1995; Murray et al. 1994). However, even small dependencies must be taken into account, as they can severely bias significance tests (Barcikowski 1981; Kreft 1994). A third source of dependence occurs within individuals when repeated measures are taken over time. In this case, the repeated measures can be considered nested within the individual.

In family-based substance use prevention research, the multilevel structure is more complicated, and dependence among observations is potentially greater. The family is both embedded within a larger context, consisting of school, neighborhood, community, and region, and also is itself a context for individual family members. Family members are likely to be much more similar than students within classrooms, and so the effect of this part of the hierarchical structure may have profound effects on research results. Furthermore, effects can take place at various levels in the hierarchy. The important concepts of risk and protective factors for substance use provide many examples of this. Attitudes toward risk taking and rebellious tendencies are examples of individual-level risk factors for adolescent substance use. Family norms about substance use is a family-level risk factor, while familial warmth and closeness are family-level protective factors. Religiosity may be both an individual-level and a family-level protective factor. Parental monitoring may be both a family-level variable and a neighborhood-level variable, because effective monitoring must occur both inside and outside the home.

Measurement Issues in Multilevel Family-Based Prevention Research

The multilevel nature of family-based research presents some interesting challenges to measurement. In family research, a latent variable may have meaning at several different levels. For example, each individual in the family has a point of view on how warm the family is. In addition, the family as a group can be rated on how warm it is. When a latent variable can be conceptualized at more than one level, there are several approaches to measurement. One is to treat the individual family member reports as indicators of the latent variable family warmth, using them to triangulate on the family-level construct. This assumes that the reports of the individual family members are all measuring the same latent variable and treats variance unaccounted for by this latent variable as error (e.g., Lorenz and Melby 1994). Alternatively, one can treat family warmth like a group of separate latent variables. There is a latent variable corresponding to each family member's point of view on warmth and another corresponding to family-level warmth. This approach assumes that the perceptions of individual family members about family warmth are worth measuring in and of themselves and that there may be valid variance in these individual reports that is not shared by the family-level latent variable.

Analytic Strategies for Multilevel Data

Multilevel phenomena can be modeled realistically by means of hierarchical linear models (Bryk and Raudenbush 1992; Goldstein 1989). Hierarchical linear models allow for the dependence among observations that results from nested data structures, and so are especially valuable for studies involving the family. Repeated measures of a criterion variable (e.g., average number of beers drunk per week in the previous month) might constitute one "level" of analysis (the within-persons or intraindividual level). A second level, the between-persons level, might consist of attributes of the person that can change (time-variant covariates such as family structure) or remain constant (time-invariant covariates such as gender). A third level of analysis could be a school-level variable such as the presence of an alcohol prevention program.

Nested data structures such as these have important implications for statistical analysis. In any hierarchical data there is likely to be dependence among observations. In other words, individuals who are sampled in a cluster will tend to be more alike in their responses than individuals who are sampled independently. Unlike the relatively low levels of dependence found in school-based research, the dependence among family members is likely to be comparatively higher. This dependence among observations is known to inflate the Type I error rate (probability of rejecting the null hypothesis when it is true) if it is not modeled in statistical analyses (Barcikowski 1981). The amount of inflation in Type I error rate is a function of the degree of dependence and the size of the clusters. In a situation where the clusters are fairly large, such as classrooms or schools, even a small amount of dependence can appreciably increase the Type I error rate.

By means of hierarchical linear models, dependence among observations can be accounted for, and growth curves for repeated measures variables can be estimated. Furthermore, interactions among variables at different levels, including interactions between growth curves and between-person and school-level variables, can be examined. For example, a researcher can test the multilevel, dynamic hypothesis that students from intact families and in schools with an alcohol prevention program have the slowest rate of increase in beer consumption. This hypothesis implies three levels of analysis: (1) at the school level, the presence or absence of a prevention program; (2) at the between-persons level, family structure; and (3) at the within-persons level, the repeated measures used to estimate the slope describing change in beer consumption over the period studied.

Several different levels of analysis are potentially relevant in family prevention research. Community-level or neighborhood-level characteristics may be important to family-based prevention efforts (Wagenaar and Perry 1994). Thus, one level of analysis taps the context of the family. A second level of analysis is present when data include information from multiple family members. Unfortunately, within-family dependence has rarely been recognized, but a notable exception is found in Barnett and colleagues' studies of distress in dual-earner couples (Barnett et al. 1993, 1995). Other levels might include between-person variables such as gender or repeated measures (for an application, see Shanahan et al., in press).

DISCUSSION

This brief overview of methodological considerations in family prevention research points to a number of generalizations for the intervention researcher. First, the complexities of prevention research require that conceptual models be specified early in the research process, ideally before the study itself has been designed (Collins 1994). Developmental research in family prevention is complicated by the dynamic and multilevel nature of families. This complexity requires rigorous theory: What is it about families that matters for substance use and why? Only specific hypotheses can point to the most appropriate methodology. At the same time, many methods require data with a specific structure (i.e., number of subjects or respondents, number and timing of observations). Thus, a conceptually based hypothesis will often dictate both the method and the type of data that are required.

Second, every research team should include a methodologist who actively participates from the very beginning of the study. This review has not covered a number of potentially relevant methods (e.g., trait-state-error models, Kenny and Zautra 1995) and has glossed over many distinctions and nuances (e.g., the differences between growth curves estimated in latent growth curve versus hierarchical linear modeling frameworks). In fact, recent advances that may be useful to prevention researchers are numerous (e.g., hierarchical latent growth-curve models, Muthén 1994) and dynamic, multilevel modeling defines a major area of methodological research.

Third, even this brief survey suggests highly useful avenues for methodological research. Because the timing and spacing of observations in a longitudinal study are so important, information that helps with this decision is very valuable. Hazard profiles for substance use prevention, such as onset across the early teen years, would be a great help to researchers designing longitudinal studies. These profiles would make it possible for researchers to time measurement and interventions for high-risk periods. Measurement is also an important area where much work is needed. More and better methodology is needed to help the prevention researcher develop sensitive and precise instruments for dynamic latent variables. Currently, hierarchical data structures are ignored by most measurement procedures. Methodology is needed for situations where there is a nested data structure, and in particular for developing instruments for latent variables that involve multiple levels. More research on establishing equivalence of measures across the lifecourse is needed also. Finally, hierarchical data structures are an issue for nonlinear models, such as survival models and latent class models. Currently these models do not incorporate nested structures; research is needed on how to generalize them in this way. Some promising research on hierarchical survival models is currently underway by Murphy (1994, 1995).

Despite the highly variable nature of contemporary family life, there is considerable evidence that the family can promote manifold dimensions of well-being, including health-related behaviors (Waite

1995). What kinds of households promote the healthy development of its members? What are the processes by which the context of the family and the family as a context matter for the well-being of children? These questions have important implications for prevention policy. The answers to them will require clearly specified developmental models and the careful application of dynamic and multilevel methods.

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