Analysis of Stage of Change
Summary and Recommendations for BCC

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A variety of statistical approaches have been taken to the analysis of stages of change as a primary or secondary intervention outcome. Some approaches are very well known; others are more obscure. Each approach has specific advantages and disadvantages.
The first two methods are recommended for the BCC projects to enable cross-site comparisons. Method 3 & 4 are presented for any interested groups.

Traditional Analytical Approaches

As a dependent outcome variable, stage of change is most commonly conceptualized as the proportion of individuals moving to the action or maintenance stages of change. This may also be thought of as the proportion of individuals at a pre-specified behavioral criterion that defines study outcome success. This approach is advantageous for several reasons: 1) it cuts across theoretical models; 2) it is generally equivalent to a bottom-line, easy to understand and easily agreed-upon measure of outcome success; and 3) it results in an essentially dichotomous outcome measure that can be analyzed using well known and widely available techniques.

The simplest analytical approaches are probably still the most commonly used, including chi-square tests and tests of proportions. Assuming all study participants are pre-action or 'at-risk' at baseline and have been randomized to treatment and control groups, the proportion reaching action or maintenance at follow-up represents an assessment of intervention outcome success. This approach assumes that the treatment and control group stage distributions are effectively equal at baseline. Stratified random assignment is often used to ensure equivalency.

While this analytical approach is very straightforward and easy to understand, there are serious disadvantages. One that is frequently overlooked is that it is usually not possible to include covariates in the analysis, at least not without difficulty and complication of what is, after all, supposed to be a relatively simple procedure. More often mentioned as the chief disadvantage of this approach involves dichotomization and statistical power. Dichotomization of the stage variable results in significant loss of information and the consequent decrease in statistical power this entails (Cohen, 1978; Rossi, 1990). Furthermore, the use of nominal level analytical procedures such as the chi-square test makes no assumptions concerning the underlying nature of the variable. However, even when dichotomized, the stage variable is at least ordinal, so that additional analytical sensitivity is lost when employing nominal level techniques. More appropriate would be the use of certain non-parametric techniques sensitive to ordinal level change over time, such as the McNemar test or the Stuart-Bowker procedure (Marasciulo & McSweeney, 19xx). Unfortunately, these procedures are obscure at best and not readily available in most

statistical computer packages. Another approach to enhancing statistical sensitivity within the confines of the more traditional analytical approaches is to employ a normalizing and variance stabilizing transformation procedure. The most appropriate procedure for proportions is the arcsine transformation (Rossi, 1985, 1990). This approach permits the use of more sensitive analytical procedures, such as the analysis of variance. For multiple group outcomes, the Levy (1975) test for pairwise comparisons among proportions – an analog of the Tukey test – is an effective follow-up procedure. The Levy procedure is also fairly obscure, but well worth seeking out.

Stage Progression Analysis

No matter what analytical approach is adopted, one disadvantage of dichotomizing stage into action vs. pre-action categories is that it fails to preserve all of the information that may be of interest in understanding how interventions are working (or not). In addition, intervention follow-up may be insufficient to capture much action, giving the impression that not much is happening. Depending on how recruitment is conducted and on the particular target behavior, it is likely that the majority of study participants will be in the precontemplation and contemplation stages of change at baseline. Movement to the action stage is therefore expected to take some time. A substitute for assessing movement to the action stage is to assess progress through the stages of change as an outcome variable. Typically this is considered a secondary outcome measure. An advantage of the use of stage progression is that it nicely mirrors the primary intervention goal of most stage-based tailored interventions, that is, to enhance motivation or accelerate progress through the stages of change.

Analysis of stage progression raises the issue of what constitutes progress. Probably the most common approach is to count all forward stage movement as progress. The result is usually again the formation of a dichotomous variable with any forward stage movement counting as progress and no movement or regression counting as no progress. A trichotomous variable is also possible though this is much less commonly done (i.e., progression vs. regression vs. no movement). In addition to raising all of the issues associated with dichotomization, another problem with this approach is that it blurs the distinction between stages since all progression counts the same, whether an individual has advanced a single stage or multiple stages.

Because progression is typically constructed as a dichotomized variable, analysis typically follows that for dichotomous variables described above (e.g., chi-square, GEE). A frequent misconception concerning the analysis of stage progression is that it will be more powerful that analyses utilizing progress to action as the outcome measure. This is not necessarily so and, in fact, stage progression analyses are often likely to be less powerful in many circumstances. This is because the proportions of individuals progressing will usually be substantially greater than the proportions reaching action for both the treatment and control groups. Thus, study outcomes are more likely to be in the vicinity of 50% than when movement to action is used as the outcome criterion. For example, in a typical smoking cessation study, the proportion reaching action in the control and treatment groups is likely to be in the 10% – 25% range. Adding any plausible constant proportion to these numbers to simulate the results of stage progression will result in outcomes closer to

50%, where statistical analyses for proportions are least sensitive (Rossi, 1985). Thus, proposing stage progression as an outcome measure will typically have the effect of requiring more subjects for any specified level of statistical power than proposing movement to action as an outcome measure.

An alternative approach to conceptualizing stage progression as a dichotomous (or trichotomous) variable would be to count the number of stages progressed as the outcome variable. For example, an individual progressing a single stage would receive a score of 1, while an individual progressing two stages would receive a score of 2, and so on. Regression to an earlier stage would be assigned negative scores. This approach would avoid the problems associated with dichotomous variable analysis and should be amenable to continuous variable techniques, such as the analysis of variance. However, this approach does not seem to be very commonly used.

Generalized Estimating Equations

More sophisticated and complex analytical approaches have also become available in recent years. A particularly powerful and versatile approach to the analysis of both continuous and categorical outcome variables employs repeated measures regression analyses under the generalized estimating equation (GEE) method to analyze intervention main effects and interaction effects (Zeger & Liang 1986). The GEE procedure provides robust estimates of population averaged effects and is especially advantageous when the objective is to make inferences about group differences. It enables use of linear, logistic and Poisson regression methods with repeated measures using minimal assumptions about time dependence, providing consistent estimates of regression coefficients and robust variance estimates even in the presence of unbalanced group data. Repeated measures analyses can be conducted with logistic regression for dichotomous outcomes (logit link function), such as stage of change, and with linear regression for normally distributed continuous outcomes (identity link function). Analytic models may include dummy variables representing the intervention groups, occasions, and intervention group by occasions interaction terms. The efficacy of the intervention is determined by the group by occasions interaction effect. In the GEE procedure, the continuous or dichotomous dependent variable with the proper link function is regressed first against treatment group, including other individual-level covariates such as age, gender, race, and education. Subsequent analytic models could then examine covariate specific treatment effects. Modeling time trends can also involve more sensitive curve fitting methods, such as the use of fractional polynomial and spline regression terms, which can provide more powerful estimates of the intervention effect over time (Greenland, 1995a, 1995b). The main disadvantage of GEE is its complexity and sophistication, so that a great deal of expertise is required to use these procedures.
Both GEE and random effects models are extensions of models for independent observations and time-dependent data, and both can be used to analyze binary outcomes longitudinally. GEE models are desirable when the research focus is on differences in population averaged response rates (i.e., treatment vs. control group differences at follow-up), and random effects models are appropriate when the emphasis is on changes in individuals' behavior across time, that is trends over time (Hu et al., 1998; Laird & Ware, 1982; Park, 1993). Both types of outcomes are usually of interest in population-based health promotion intervention studies. Thus, analyses of

primary treatment–control group differences utilize GEE models, while analyses of rates of behavior change over time may profitably employ random effects logistic models. Random effects models have a key advantage for handling missing data because subjects are not assumed to be measured at the same number of time points, thus subjects with missing data on the dependent variable are not excluded from the analysis (Hedeker & Gibbons, 1997; Little, 1995). Random effects models are also less restrictive with respect to missing data assumptions than GEE and, realistically, allow missingness to depend upon an individual's previously observed values of the dependent variable (Hu et al., 1998). An additional advantage is that both individual and cluster level variables can be included in the analysis.

Other powerful statistical approaches, including hierarchical linear modeling, structural equation modeling, and latent growth curve modeling are currently being investigated but as yet have seen relatively little use in the analysis of intervention outcome data, especially for dichotomous or stage-like variables.

Latent Transition Analysis

A relatively new and powerful approach to the analysis of movement through the stages of change is latent transition analysis (LTA; Collins & Wugalter, 1992; Graham et al., 1991; Martin et al., 1996). Similar in some respects to structural equation modeling (SEM), LTA is most appropriate for a stage model that specifies a transitional order among the categories and provides an underlying theoretical model. Because it is sensitive to the whole range of possible transitions in stage of change membership, LTA is an ideal approach for the assessment of stage movement. Effective interventions should increase the probability of forward transitions through the stages of change, decrease the probability of backward transitions, or both.

As in SEM, LTA relies on a latent variable conceptualization of the target constructs. Stage of change can be conceptualized as a construct that is not directly observable, but rather is inferred from one or more manifest variables, such as the stage of change algorithm. These unobserved constructs organize observed manifest variables and are either static or dynamic (Collins & Cliff, 1990). Latent variables represent general constructs that are best measured with multiple manifest indicators. Dynamic variables involve systematic change over time while static latent variables are unchanging. Conceptualizing stage as a dynamic latent variable can clarify who is likely to progress or regress. A substantial advantage of such an approach is the ability to detect intervention effects much earlier than more traditional analytical approaches. It also allows for the analysis of patterns of change and the detection of differential treatment effects for different stages. LTA is therefore useful for answering a variety of research questions that are likely to be of interest to researchers: 1) to test alternative theoretical models about the pattern of change over time; 2) for comparing different groups to test for treatment effects; 3) for evaluating the contribution of different measures for each latent status or construct; 4) for identifying the distribution of subjects by latent status at each occasion; and 5) for planned comparisons to address specific process-oriented research questions. For example, a researcher might want to see if an intervention is more effective for individuals in one stage compared with another. Alternatively, the

transition probabilities for Time 1 to Time 2 can be compared to the transition probabilities for Time 2 to Time 3 to see if the effects of the intervention are changing over time.

The most widely employed analysis technique for examining discrete latent variables is latent class theory (LCT). LCT is a method for looking at static latent variables that permits estimation of measurement error in the model. In latent class measurement theory (Clogg & Goodman, 1984; Dayton & Macready, 1976; Lazarfeld & Henry, 1968) discontinuous latent variables are measured by observed responses, usually dichotomous, to a manifest indicator variable. Latent class membership is mutually exclusive and each member of a population is classified into one and only one of several latent classes. Latent class theory is limited, however, because it does not handle dynamic latent variables that change systematically over time (Graham et al., 1991). Markov models are a special latent class procedure for stage-sequential dynamic latent variables. Markov procedures may be used for predicting the probability of movement through stages over a specific time interval. Markov models are the most widely employed technique for examining discrete dynamic variables longitudinally
Traditional measurement and analysis developed for static variables suffer from serious shortcomings when applied to dynamic variables (Collins & Cliff, 1990). The advantage of LTA is that it extends the LCT and Markov techniques to models that contain both static and dynamic latent variables and includes an estimation of measurement error. In addition, LTA emphasizes the use of multiple indicators (Collins & Wugalter, 1992) allowing testing of complex models. LTA can be performed using a FORTRAN program (Collins et al., 1991, 1998) that uses the expectation-maximization (EM) algorithm (Dempster, Laird, & Rubin, 1977) for estimating four types of parameters: 1) the gamma parameters (γ), which are estimates of the proportion of the population in each latent class (discrete grouping variable); 2) the delta parameters (δ), which are estimates of the proportion of the population in each latent status (or stage) at each occasion of measurement, conditional on latent class membership; 3) the tau parameters (τ), which refer to the conditional probability of transitioning from one latent status (stage) conditional on previous latent status membership and latent class; and 4) the rho parameters (ρ), which represent measurement error and are estimates of a particular item response conditional on latent status and latent class membership. A recently released version of the program (Collins et al., 1998) includes a more user-friendly Windows operating system and provides estimates of the standard error terms for parameter estimates.

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LTA Extra

A schematic representation of a transition probability matrix for a stages of change example appears in Table 1. The rows and columns correspond to the five latent statuses in the Stages of Change model. All of the elements in this matrix are conditioned on membership in a Treatment condition. Although it is not shown here, there would be another transition probability matrix for the Control condition. The values on the diagonal of this matrix represent stability or the probability of remaining in the same latent status (assuming no one leaves a latent status and returns to it between observations). For example, the element $T_{PC/PCt}$ is the probability of membership in the Precontemplation stage on the second occasion, conditional on membership in the Precontemplation stage on the first occasion and membership in the Treatment condition. Values above the diagonal of the transition probability matrix represent progression or the probability of moving forward to an advanced stage. Values below the diagonal represent regression or the probability of moving backward to a previous stage. If according to the model being tested movement among stages can be either forward or backward, all elements of the transition probability matrix are estimated. This is what is shown in Table 1. If according to the model certain kinds of transitions are not possible, the user can fix elements of the transition probability matrix to zero as appropriate. For example, if the two occasions of measurement are only four months apart, it is not possible to move from the contemplation stage to the maintenance stage, because the action stage between them is defined as a six month period. Therefore, $T_{M/Ct}$ would be fixed at zero.

Table 1
Full Tau Parameter Matrix for Stages of Change

	Stage at Occasion 2				
Stage at Occasion 1	PC	C	P	A	M
Precontemplation	$\tau_{PC\|PC,LC}$	$\tau_{C\|PC,LC}$		$\tau_{P\|PC,LC}$	$\tau_{A\|PC,LC}$ $\tau_{M\|PC,LC}$
Contemplation	$\tau_{PC\|C,LC}$	$\tau_{C\|C,LC}$	$\tau_{P\|C,LC}$	$\tau_{A\|C,LC}$	$\tau_{M\|C,LC}$
Preparation	$\tau_{PC\|P,LC}$	$\tau_{C\|P,LC}$	$\tau_{P\|P,LC}$	$\tau_{A\|P,LC}$	$\tau_{M\|P,LC}$
Action	$\tau_{PC\|A,LC}$	$\tau_{C\|A,LC}$	$\tau_{P\|A,LC}$	$\tau_{A\|A,LC}$	$\tau_{M\|A,LC}$
Maintenance	$\tau_{PC\|M,LC}$	$\tau_{C\|M,LC}$	$\tau_{P\|M,LC}$	$\tau_{A\|M,LC}$	$\tau_{M\|M,LC}$