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Latent Transition Ananlysis as a Sensitive Outcome: Analysis for Longitudinal Data

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LATENT TRANSITION ANALYSIS AS A SENSITIVE OUTCOME
ANALYSIS FOR LONGITUDINAL DATA

BY

ROSEMARIE A. MARTIN

A DISSERTATION SUBMITTED IN PARTIAL FULLFILLMENT OF THE
REQUIREMENTS FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY
IN
PSYCHOLOGY

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2003

DOCTOR OF PHILOSOPHY DISSERTATION

OF

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APPROVED:

Dissertation
Committee:

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The image shows five handwritten signatures, each on a horizontal line. From top to bottom, the signatures are: Wayne Velton, Geoffrey W. Greene, James D. Anderson, Joseph L. Foy, and Harold D. Bibb.

DEAN OF THE GRADUATE SCHOOL

UNIVERSITY OF RHODE ISLAND

2003

ABSTRACT

Three secondary data analysis studies were conducted to provide methodological and theoretical examples of the application of Latent Transition Analysis (LTA) to three studies of smoking cessation among adults. Each study was designed to evaluate an interactive expert system intervention for smoking cessation in three different populations of smokers: (1) Chapter 2 evaluated the expert system intervention versus assessment only in smokers from the state of Rhode Island (N=4,144); (2) Chapter 3 evaluated the expert system intervention versus a non-interactive manual-based intervention in a managed care setting (N=2,882); (3) and Chapter 4 examined the expert system intervention versus assessment only for high school students' parents (N=2,461) who were receiving interventions for up to three problem behaviors simultaneously. LTA in each study consisted of four parts: model specification, descriptive analyses of parameter estimates, tests of differential treatment effects using data augmentation procedures, and a descriptive process analysis. Major findings are: (1) The expert system intervention has better outcomes in terms of stage of change than the control conditions as evidenced by more progression to later stages and less regression to early stages; (2) The expert system intervention is particularly effective for the Precontemplation and Contemplation stages proximal to intervention delivery, while the effects weaken over time; (3) Data augmentation procedures lack sensitivity for detecting treatment effects. Recommendations are made for future research in this area.

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Chapter 1

Latent Transition Analysis: A Sensitive Outcome Analysis for Longitudinal Data

There is a growing need for theory driven research and treatment development to understand the complex process of behavior change. Models of behavior change introduce a theory to explain variance in behavior change and provide not only outcome information but include critical process measures which help determine how, when, and why interventions are effective. A theory of behavior change includes a predictable pattern of relationships between a set of variables, ideally, culminating in mathematical relationships (Prochaska & Velicer, 1996). Useful theories of behavior change prompt important research findings and are useful in designing and implementing treatments (Hughes, 1996). The research findings guide development of effective treatments that are evaluated with theory driven a priori predictions.

Outcomes alone do not explain why a treatment does or does not work. Questions about treatment effectiveness cannot be completely answered, even with significant outcome results unless process evaluation can be used to support hypothesized mechanisms of action (DiClemente, Carrol, Connors & Kadden, 1994). There is growing appreciation of the need for process assessment. Researchers are concerned with developing effective interventions and rigorous methodologies for testing them and demonstrating the conditions under which they are useful (Mattson & Donovan, 1994). Theory driven research based on well-

supported models must be conducted to improve our understanding of when, how and for whom behavior change occurs.

The transtheoretical model (TTM; Prochaska & DiClemente, 1983) is a general model for health behavior change that has been well supported in empirical research. The TTM has been successfully applied to a variety of behaviors and has demonstrated systematic relationships among model constructs. The TTM construct, stage of change, is the temporal organizational component, and at any one time, a person is in one of the five stages of change (Precontemplation, Contemplation, Preparation, Action, and Maintenance). Recent advances in methodology improve our ability to incorporate measures traditionally thought of as outcome measures, e.g. stage of change, into process analyses. One recent advancement is Latent Transition Analysis (LTA; Collins, Wugalter, & Rousculp 1991; Collins, Lanza, Schafer, & Flaherty, 2002) a method of analyzing categorical dynamic latent constructs over time.

The current study will replicate and extend previous applications of LTA to the stages of change for smoking cessation. Three separate secondary analysis studies will apply LTA to stage of change data and consist of four parts: model specification, examination of parameter estimates, test of differential treatment effects, and a descriptive process analysis. A review of the LTA and the stages of change for smoking are provided and a detailed description of the methodology and procedures used in the studies.

Latent Transition Analysis: Overview

In the study of behavior change the focus of study often is a latent construct that is not directly observable, such as stage of change. Latent constructs can be measured univariately or multivariately with several manifest indicators change and are either static or dynamic (Collins & Cliff, 1990). Dynamic variables involve systematic change over time while static latent variables are unchanging. Traditional measurement and analysis developed for static variables suffer from serious shortcomings when applied to dynamic variables (Collins & Cliff, 1990).

A widely employed analysis technique for examining discrete latent variables is latent class theory (LCT, Clogg & Goodman, 1984; Dayton & Macready, 1976; Lazarfeld & Henry, 1968). LCT is a method for looking at static latent variables that permits estimation of measurement error in the model. In Latent Class Measurement Theory Latent class membership is defined by the response to the manifest indicator, is mutually exclusive, and each member of a population is classified into 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, Collins, Wugalter, Chung & Hansen, 1991). Markov Models are a special latent class procedure for stage-sequential dynamic latent variables measured longitudinally. Markov procedures are used for predicting the probability of movement through stages over a specific time interval.

Latent transition analysis (LTA) extends LCT to include latent status measured by dynamic latent variables, and examines movement among the latent

statuses over time. As with LCT, LTA contains parameters that represent the possible error of the manifest items. Latent class is measured only once and does not change, i.e., gender or treatment condition. In contrast, latent status is measured a minimum of two occasions and is expected to change over time.

The stages of change involves five latent statuses which are: 1) Precontemplation (PC); 2) Contemplation (C); 3) Preparation (PR); 4) Action (A); and 5) Maintenance (M).

The Latent Transition Analysis Model and Notation. The model is most easily understood with an example. Assume there are two occasions of measurement, five latent statuses, and a static latent variable with two latent classes. The occasions of measurement will be defined as *time t* for the first and *time t+1* for the second. Latent status, represented by *S*, will be defined as PC for the first latent status, C for the second latent status, PR for the third latent status, A for the fourth latent status and M for the final latent status. *S1* will represent latent status at time 1 and *S2* will represent latent status at time 2. Assume that latent status is measured by five items, *item 1*, *item 2*, *item 3*, *item 4*, and *item 5* where *g*, *h*, *i*, *j*, *k*, equal responses at *time t* and *g'*, *h'*, *i'*, *j'*, *k'* equal responses at *time t+1*. Lastly, assume that latent class, treatment condition (intervention or control) is measured by one item where *m* equals the response to the item. Therefore, each participant will have a vector of response patterns (*Y*) for each of the measured variables where $Y=\{m, g, h, i, j, k, g', h', i', j', k'\}$.

LTA models involve four different types of parameters: 1) the gamma parameters (γ), which are estimates of the proportion of the population in each latent class, 2) the delta parameters (δ), which are estimates of the proportion of the population in each latent status at each occasion of measurement, 3) the tau parameters (τ) which refer to the conditional probability of transitioning from one latent status to another, and 4) the rho parameters (ρ), which represent measurement error, that are estimates of a particular item response conditional on latent status and latent class membership. The formal mathematical equation for the LTA model is represented by:

$$[1] \gamma_{LC} \rho_{M|LC} \delta_{S|LC} \rho_{g|S1,LC} \rho_{h|S1,LC} \rho_{i|S1,LC} \rho_{j|S1,LC} \rho_{k|S1,LC} \tau_{S2|S1,LC} \rho_{g'|S2,LC} \rho_{h'|S2,LC} \rho_{i'|S2,LC} \rho_{j'|S2,LC} \rho_{k'|S2,LC}$$

The gamma parameters (γ_{LC}) represent the proportion in each latent class. The number of γ 's estimated freely is $C-1$ where C is the number of latent classes. Latent class typically does not change across occasions of measurement. The latent class could be the result of an experimental manipulation such as an intervention condition or a naturalistic grouping variable such as gender or grade level.

The delta parameters ($\delta_{S|LC}$) are the proportion of the population in each of the five latent statuses at each occasion of measurement conditional on latent class membership. There is one delta for each latent status at each occasion of measurement for each latent class. In this example the $\delta_{S|LC}$ is a vector.

$$[2] \quad \delta_{S|LC} = \begin{bmatrix} \delta_{PC|LC} \\ \delta_{C|LC} \\ \delta_{PR|LC} \\ \delta_{A|LC} \\ \delta_{M|LC} \end{bmatrix}$$

Where $\delta_{PC|LC}$ is the proportion in the Precontemplation stage, $\delta_{C|LC}$ is the proportion in the Contemplation stage, $\delta_{PR|LC}$ is the proportion in the Preparation stage, $\delta_{A|LC}$ is the proportion in the Action stage, and $\delta_{M|LC}$ is the proportion in the Maintenance stage. The number of freely estimated δ parameters is equal to $C(S-1)$, in this example $2(5-1)$ or 8. Examination of the delta parameters shows the growth or decline in latent status membership over time. The proportions in PC, C, and PR should decrease and A and M should increase over time when there is engagement in positive behavior change.

The tau parameters ($\tau_{S2|S1,LC}$) matrix is the transition probability matrix representing the probabilities of transitioning to each of the latent statuses at time 2 conditional upon membership in a particular latent status at time 1 and latent class. The τ 's form the transition probability matrix and is an SXS matrix. When movement among stages can be either forward or backward, there is a full probability matrix. If we assume two occasions of measurement the $5X5$ -transition probability matrix for the stages of change would be represented as:

$$[3] \quad \begin{matrix} & \text{Occasion 2} \\ \text{Occasion 1} & \begin{bmatrix} \tau_{PC|PC} & \tau_{C|PC} & \tau_{PR|PC} & \tau_{A|PC} & \tau_{M|PC} \\ \tau_{PC|C} & \tau_{C|C} & \tau_{PR|C} & \tau_{A|C} & \tau_{M|C} \\ \tau_{PC|PR} & \tau_{C|PR} & \tau_{PR|PR} & \tau_{A|PR} & \tau_{M|PR} \\ \tau_{PC|A} & \tau_{C|A} & \tau_{PR|A} & \tau_{A|A} & \tau_{M|A} \\ \tau_{PC|M} & \tau_{C|M} & \tau_{PR|M} & \tau_{A|M} & \tau_{M|M} \end{bmatrix} \end{matrix} = T$$

There is one tau matrix for each occasion of measurement and each latent class.

The number of parameters estimated freely is equal to $S(S-1)(T-1)$ where T is the number of occasions of measurement, in this example $5(5-1)(2-1)$ or 20..

The diagonal elements of the tau matrix represent stability, i.e., the proportion of individuals who remain in the same latent status on both occasions of measurement. The elements above the diagonal represent progression. These values represent the proportion of individuals who move forward to a new latent status on the second occasion. The elements below the diagonal represent regression, i.e., the proportion of individuals who move backward to a previous latent status on the second occasion.

There are two sets of rho parameters (ρ); one associated with the static latent variable representing latent class membership and one associated with the dynamic latent variable representing latent status membership. The rho's (ρ) represent the probability of a particular response to each manifest variable at each occasion of measurement conditional on latent class membership and/or latent status membership. The measurement parameters ($\rho_{LS|LC}$) represent the probability of responses to the item measuring the static latent variable conditional on latent class membership. It is the probability a member of latent class 1 will select the first response category.

The rho parameters associated with the dynamic latent variable represent the probability of response to the item measuring the dynamic latent variable conditional on latent status membership and latent class membership. The

elements of the rho matrix represent the probability that members in a particular stage and latent class will select a particular response category. For example $\rho_{g|PC,LC}$ represents the probability that members of the Precontemplation stage that belong in latent class 1 will respond with category one, or yes, to the first item measuring the dynamic latent variable.

The ρ 's serve two roles in the LTA model. The ρ 's map the manifest item onto the latent statuses as factor loadings show the relationship between items and a factor. And the ρ 's also show how precisely the manifest items measure the latent variables. The rho parameters can be interpreted as representing the relationship between the manifest variables and latent classes in the same way the factor loadings relate the manifest variables to the latent factors in structural equation modeling. The values close to zero or one indicate that the manifest response is determined by latent status membership and values that are close to one divided by the number of response patterns are determined by chance. The parameters associated with the latent class variable that can be estimated freely are $CI(M-1)$ where I is the number of manifest variables measuring the latent static variable and M is the number of response categories for each manifest variable. The parameters associated with the latent status variable that can be estimated freely are $CSTJ(M-1)$ where J is the number of manifest variables measuring the dynamic latent variables.

LTA allows for incomplete data and provides a routine for the missing data based on computational techniques developed to handle missing data in

contingency tables (Schafer, 1997). The missing data estimation procedure is robust when the data are missing completely at random (MCAR) or missing at random (MAR) according to a simulation study (Hyatt & Collins, 1998). The user specifies whether or not the data set contains missing data.

Model Specification and Model Comparison

LTA can be used to specify alternative models and determine how well a particular model fits the data. A model predicts the number of people who will contribute to a particular response pattern. A good fitting model will have predictions that are close to the actual data. The goodness of fit statistic will be small relative to degrees of freedom for a good fitting model (Graham et al., 1991). G^2 , a likelihood-ratio goodness-of-fit statistic, is approximately distributed as a chi-square where degrees of freedom is equal to the number of response patterns (K) minus the number of estimated parameters (P) minus one or expressed $df = K - P - 1$. Formal hypothesis testing for model specification can be difficult with latent class models because with complicated or large models the multiway contingency table can become sparse or contain empty cells. Under these conditions, the distribution of the G^2 statistic is not approximated by the chi-square (Collins, Fidler, Wugalter & Long, 1993). The distribution of the G^2 difference for nested models may be more robust in general (Agresti & Yang, 1987; Haberman, 1977), but monte carlo studies indicate this not true of latent class models (Holt & Macready, 1989). Because latent class models rely on the G^2 with all the attendant problems, crossvalidation is particularly useful when specifying models. Cudeck &

Brown (1983) recommend a double crossvalidation approach to model selection. This involves identifying a set of plausible models, estimating parameters separately in each half of a randomly split sample, and then computing two fit indices by applying each model as fitted in one half to the opposite half of the sample. The crossvalidation fit indices are examined and the model with the best indices is selected.

Significance Testing of Parameter Estimates in LTA

LTA provides parameter estimates based on two different techniques. Each technique provides separate estimates of latent transition model parameters. Until recently LTA used the Estimation Maximization (EM; Dempster, Laird, & Rubin, 1977) algorithm to produce maximum likelihood estimates for latent transition models. The maximum likelihood solution, however, does not provide standard errors. Recent advances in the LTA software (Collins, Schafer, Hyatt, & Flaherty, in preparation; Hyatt, Collins, & Schafer, 1999; Brunner, & Schafer, 1997) now use an Empirical Bayes approach, using data augmentation (DA; Schafer, 1997) for obtaining standard error estimates. Standard error estimates are useful in two ways: they provide a measure of uncertainty for each parameter estimate and they allow for hypothesis testing. Significance tests for differences between parameter estimates can be conducted based on the DA estimates and standard errors.

DA uses a Markov Chain Monte Carlo approach to the analysis of incomplete data. DA treats the latest variables as missing data and simulates this unknown data repeatedly, a technique called multiple imputation. Standard errors

are calculated based on multiple draws of the data. The EM algorithm operates by alternately predicting the missing data in the E step and re-estimating the parameters in the M step. DA operates similarly but with random noise added. DA alternately simulates the data in the imputation step and the parameters in the posterior step. A Markov chain is created that converges in distribution to the joint predictive distribution of the missing data and parameters (Schafer, 1997). DA is run for many cycles and multiple draws of missing data from the posterior distribution of parameters are obtained. The process repeats resulting in multiple independent draws of missing data, or in the case of latent transition models, multiple draws of the latent parameters. For WinLTA 3.0 (Collins, Lanza, Schafer, & Flaherty, 2002) the user specifies the number of cycles between each draw and the total number of draws to make. Each draw contains imputed data for latent classes and latent statuses as specified by the latent transition model. Standard data techniques can then be used to analyze each data set to obtain a point estimate and within-imputation variance for each parameter estimate.

Hypothesis testing of LTA parameters can be performed using differences of proportions or relative risk ratios. For differences of proportions, the null hypothesis of no difference is rejected if the confidence interval for difference does not contain zero. The multiple imputation combination rule of Rubin (1987) is used to average across the imputations. This rule combines differences of proportions or relative risks and the associated within-imputation variances across the draws of data to estimate the average point estimate, the overall amount of

variance, and the 95% confidence interval (CI) for each statistic. This allows for the comparison of parameter estimates between groups or comparison of parameter estimates within groups. The averaging across imputations is done using SAS (SAS User's Guide, 1994). The technical details of conducting hypothesis testing are found in Hyatt, Collins, & Schafer (1999).

Examples of LTA Applications

LTA has been used to test two alternative models of adolescent substance use onset and examine a school based substance use prevention program on adolescent substance use (Graham et al., 1991). First, a model of substance use onset including both alcohol and cigarette use as possible starting points fit better than a model that included alcohol use only as the starting point. Second, students who had smoked cigarettes but not used alcohol in seventh grade were on an accelerated substance use onset trajectory. Third, results indicate that those seventh graders who received a normative education curriculum had a significantly better outcome than those seventh graders who did not, except for the students who had tried cigarettes only in seventh grade. Better outcome was marked by no transition to a higher use latent status or transition into a lower use latent status (Graham et al., 1991).

LTA has also been used examine math skills acquisition from sophomore to senior year, using a cohort of 1500 students in their sophomore year and beyond (Rock & Pollack, 1987). Participants' math skills were tested and found to be in one of five latent statuses: 1) no skill, 2) single operations on whole numbers, 3)

single operations and powers and roots, decimals and fractions, 4) single operations, powers and roots, and low level algebra, and 5) single operations, powers and roots, low-level algebra and low-level geometry, algebra with word problems. Three alternate models were tested, learning without unlearning, learning and unlearning, and neither learning nor unlearning. The first model, learning without unlearning, was found to fit the data best.

Crossvalidation of LTA models were used to select models of early substance use in a sample of adolescents (Collins, Graham, Long & Hansen, 1994). Five models of substance use onset were compared for males and females separately using crossvalidation procedures (Cudeck & Browne, 1983). The same model crossvalidated well for both males and females indicating that the nature of the substance use onset process is the same for males and females. A series of multiple group models were conducted where constraints were systematically imposed on parameters (Joreskog, 1971). The results suggests that the rate of movement through the substance use process is the same for males and females, however there is evidence for gender differences in substance use experience at the beginning of the seventh grade, with males more advanced in the onset process.

The acquisition and maintenance of safer sexual behavior among injection drug users was examined by comparing a five stage versus a six-stage model (Posner, Collins, Longshore & Anglin, 1996): 1) High risk, 2) knowledge only, 3) safe sex only, 4) sex risk, low risk, but denial, and 5) low risk. There was much movement in and out of the stages over time and the composition of the low-risk

group changed considerably. Injection drug users appear to move back and forth among high, medium and low risk stages.

Several studies have applied LTA to longitudinal stage of change data. LTA was used to test three alternative models of transitions among the stages of change for smoking cessation (Martin, Velicer & Fava, 1996). The models assessed movement among the stages for a two-year period. The model that fit the data best indicates that in a six-month period both progression and regression among the stages takes place as well as two-stage progression. Examination of the probability of movement among the stages revealed three findings consistent with the Transtheoretical Model. First, movement through the stages is not always linear. Second, the probability of forward movement is greater than backward movement. Third, the probability of moving to adjacent stages was greater than probability of two-stage progression.

A second study applied LTA to longitudinal stages of change for condom use in women (Evers, Harlow, Redding, & LaForge, 1998). Six models of movement through the stages of condom use over a one-year period were compared. The model which included both backward and forward movement of one, two and three stages, in addition to relapse from Maintenance to Precontemplation fit the data best. Precontemplation and Maintenance were found to be the most stable stages, and the Action stage the least stable. There is a high rate of relapse in condom use.

Transtheoretical Model: Stage of Change as an Outcome Variable

The Transtheoretical Model (TTM) includes the stages of change as a temporal organizational structure; a set of independent variables that include processes of change and levels of change; dependent variables that include pros and cons of change, self-efficacy and temptation; and environmental variables and behaviors specific to the problem area. Systematic relationships between these variables exist that produce useful integration (Prochaska, DiClemente, Velicer, & Rossi, 1992, Prochaska et al., 1994). The TTM has been successfully applied to a wide variety of areas. The area of smoking cessation has been studied extensively and results have been replicated repeatedly. A predictable pattern of relationships between TTM variables has been tested with 40 separate theory driven predictions for the area of smoking cessation (Velicer, Norman, Fava, & Prochaska, 1999).

The definitions of the stages employ both behavior and behavioral intention. A person with a maladaptive behavior is at any one time in one of five stages of change with respect to that behavior: Precontemplation (no intention to change in the future), Contemplation (seriously thinking about changing in the near future but without commitment yet), Preparation (intend to take Action within the next month and have made an attempt to change the behavior in the past year), Action (has been abstinent for a certain length of time; at least 24 hours for cigarettes), and Maintenance (has successfully changed the target behavior for at least 6 months) (Prochaska et al., 1992; DiClemente, Prochaska, Fairhurst, Velicer, Velasquez, & Rossi, 1991). Longitudinally, people often do not progress steadily

through these stages; some stay at one stage while others relapse and cycle back. A recent review of data across 12 different problem behaviors found that these stages predict the degree of change, the perceived pros and cons of the behavior, and the processes or methods of change used by the clients (Prochaska et al., 1992 and 1994).

The argument for measuring outcome for behavior change from a stage perspective rather than a single manifest variable perspective has been demonstrated in the area of smoking cessation (Velicer, Prochaska, Rossi, & Snow, 1992). Traditionally, researchers have depended on criterion measures that have cursory face validity but suffer from some severe limitations including lack of precise definitions, poor statistical power, and lack of meaningfulness for some aspects of the problem. These problems with traditional methods of examining outcomes over time may produce results that are misleading. The three self-report measures most widely employed for smoking cessations are point prevalence, continuous abstinence, and prolonged abstinence. From the stage of change view, these measures have severe limitations in that they are based on an action paradigm where behavior is viewed as dramatic and discrete movement from smoking to nonsmoking (Prochaska, Velicer, Fava, Rossi, & Tsoh, 2001a).

Point prevalence is the foremost employed outcome measure in smoking cessation and reflects the percentage of participants not smoking at a particular point in time. Various abstinence criterions may be used for point prevalence, for example, 24 hours, 7 days, or a longer period. The more liberal the criterion the

more people will be counted as having a favorable outcome. From a stage perspective, point prevalence reflects the percentage taking Action for smoking at a particular point in time. The longer the abstinence criterion required the longer the individual will be in the Action stage prior to meeting the point prevalence criterion for not smoking. Point prevalence outcome compares the Precontemplation, Contemplation, and Preparation stages combined with the Action and Maintenance Stages combined. It ignores all stage transitions except the transition from Preparation to Action. Typically, only 20% of smokers are in the Preparation stage (Velicer, Fava, Prochaska, Abrams, Emmons, & Pierce, 1995), and the point prevalence measure, therefore, would be insensitive to change for the remaining 80% of smokers.

Prolonged abstinence is the proportion of participants who have progressed to the Maintenance stage at any point in time. The longer the abstinence criterion required for prolonged abstinence the longer the individual will be in the Maintenance stage prior to meeting the prolonged abstinence criterion. Prolonged outcome compares the Precontemplation, Contemplation, Preparation, and Action stages combined with the Maintenance stage. It ignores all stage transitions except the transition from Action to Maintenance, and may not even include all who make this transition depending on the period of abstinence required.

Continuous abstinence reflects the proportion of participants who have progressed to Maintenance in a linear fashion with no regression to a previous stage. Continuous abstinence outcome compares those who progress from

Precontemplation or Contemplation to Action to Maintenance without lapsing. It ignores all stage transitions that do not follow a linear pattern. A small minority of contemplators (5%) follows a linear pattern and do not relapse from Contemplation to Maintenance (Prochaska, Velicer, Guadagnoli, Rossi & DiClemente, 1991). Continuous abstinence is insensitive to change for the remaining 95%.

It is unlikely that those in early stages will reach any of the action paradigm criterion behaviors described above and remain abstinent in a short time frame, but effective interventions with early stage smokers will result in changes in point prevalence in an extended follow-up, such as 18 or 24 months post-intervention, (Prochaska, DiClemente, Velicer, & Rossi, 1993).

This is particularly important in smoking research where participants may make some changes during each follow-up period, but not enough change to be considered abstinent. Interventions must facilitate four transitions: 1) Precontemplation to Contemplation, 2) Contemplation to Preparation, 3) Preparation to Action, and 4) Action to Maintenance. Our outcome measures must also be sensitive to these transitions between stages. Analysis of stage movement would be able to detect intervention effects earlier by examining change among the earlier stages of change (e.g. Precontemplation and Contemplation). It would also allow analysis of the pattern of change and detection of differential treatment effects for different stages and the pattern of the differential effects over time. These types of analyses are essential for refining our research and treatment models.

Summary of the Research Completed for this Dissertation

Three separate studies provide empirical examples of the application of LTA to three studies of the stages of change and smoking cessation among adults. The three studies are presented as three independent manuscripts, therefore, this some repetition of content and structure within the studies. The applications of latent transition methodology to the stages of change will be informative on two levels: methodological and theoretical. First, because the stage of change model is well researched and understood, it provides a platform to which the strengths and limitation of the latent transition methodology may be studied. Therefore, one can gauge the usefulness of LTA in contributing unique information to a well-studied phenomenon. Second, the applications to the stages of change will provide a more detailed picture of how people change over time as compared to what is found using traditional data analytic techniques. The studies will demonstrate the types of information obtained using LTA and the utility of LTA for examining group differences.

The aim of the current study is to replicate and extend previous applications of LTA to the stages of change. Previous studies have applied LTA to stages of change for smoking cessation in the adult population (Martin, Velicer & Fava, 1996; Velicer, Martin & Collins, 1996). These studies have been descriptive; identifying a model which best describes movement among the stages, the stability of stage membership over time, and the probability of movement among the stages. The current study proposes to replicate previous descriptive findings and extend

this program of research in two ways. First, LTA will be applied inferentially using data augmentation procedures to examine differential treatment effects for stage-matched interventions versus control conditions for smoking cessation in three samples of adult smokers. Second, the analysis of stage transitions over time will be examined as a process evaluation.

Each study is a secondary analysis of existing data and is parallel in structure consisting of four parts. The first part identifies a model which best describes movement among the stages over time. The second part presents descriptive analysis of DA parameter estimates for the specified model. The third part examines differential treatment effects using statistical tests for group differences. The fourth part provides an example of how LTA data can be examined as a process evaluation. A final discussion following the third study examines the extent to which the three studies' results replicate and the utility of employing LTA to assess differential treatment effects and as a process analysis.

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Chapter 2

Evaluating an Expert System Intervention for Smoking Cessation in a Population Based Sample

Traditional clinical trials have been invaluable to our understanding clinical phenomenon. However, in order for science to progress, a paradigm shift is required (Prochaska, Velicer, Fava, Rossi, & Tsoh, 2001). Consistent with this shift, researchers must rethink basic research methods including recruitment approach, definitions of meaningful outcomes, appropriateness of interventions, and the method of analysis for population-based trials. Decisions in one of these areas would affect decisions in the other areas.

The most common approach for recruitment for clinical trials has been a reactive approach where subjects are informed of the availability of an intervention program and must contact the program to participate. Reactive recruitment results in low participation rates, typically 1-5% (Schmid Jeffrey, & Hellerstedt, 1989). A proactive recruitment approach contacts the subjects directly and offers the services to them. Proactive recruitment results in higher participation rates. The interventions that have the highest efficacy for smoking cessation also have the lowest participation rates. Conversely, the clinical trials with the highest participation rates also have the lowest abstinence rates. Both of these programs result in low impact (Velicer & DiClemente, 1993, Velicer & Prochaska, 1999). What the field needs are interventions that can maximize participation rates without sacrificing abstinence rates (Prochaska et al., 2001). From the stage of change

perspective, both these programs have severe limitations in that they are based on an action paradigm where behavior is viewed as dramatic and discrete movement from smoking to nonsmoking (Prochaska et al., 2001). Prior research demonstrates that at most 20% of smokers plan to quit in the next month and have tried to quit in the past year (Velicer Fava, Prochaska, Abrams, Emmons, & Pierce, 1995).

In retrospective, cross-sectional, and longitudinal studies of how people quit smoking on their own, evidence indicates that smokers move through a series of stages of change in their attempts to quit smoking (DiClemente & Prochaska, 1982; Prochaska & DiClemente, 1983; Prochaska, DiClemente, Velicer, Ginpil, & Norcross, 1985). A smoker is at any one time in one of five stages of change with respect to quitting smoking: Precontemplation (not thinking about quitting smoking in the next 6 months), Contemplation (seriously thinking about quitting smoking in the next 6 months), Preparation (seriously thinking about quitting smoking in the next month and have made an attempt to quit smoking in the past year), Action (making overt changes to stop smoking and lasts 0-6 months), and Maintenance (has successfully quit smoking for at least 6 months) (Prochaska, DiClemente, & Norcross, 1992; DiClemente, Prochaska, Fairhurst, Velicer, Velasquez, & Rossi, 1991). Longitudinally, people often do not progress steadily through these stages; some stay at one stage while others relapse and cycle back.

The argument for measuring outcome for behavior change from a stage perspective rather than a single manifest variable perspective can be seen in the area of smoking cessation (Velicer Prochaska, Rossi, & Snow, 1992). The three

self-report measures most widely employed for smoking cessation are point prevalence, continuous abstinence, and prolonged abstinence. These criterion measures have cursory face validity but suffer from some severe limitations including lack of precise definitions, poor statistical power, and lack of meaningfulness for some aspects of the problem. The most widely employed measures of smoking outcome are insensitive to change for 80% to 95% of smokers.

Traditional methods of examining these outcomes over time may produce results that are misleading. It is unlikely that those in early stages will reach any of the action paradigm criterion behaviors described above and remain abstinent in a short time frame, but effective interventions with early stage smokers will result in changes in point prevalence in an extended follow-up, such as 18 or 24 months post-intervention, (Prochaska, DiClemente, Velicer, & Rossi, 1993). This is particularly important in smoking research where participants may make some changes during each follow-up period, but not enough change to be considered abstinent. Interventions must facilitate four transitions: 1) Precontemplation to Contemplation, 2) Contemplation to Preparation, 3) Preparation to Action, and 4) Action to Maintenance. Our outcome measures and method of analysis must also be sensitive to these transitions between stages. Analysis of stage movement would be able to detect intervention effects earlier by examining change among the earlier stages of change (e.g. Precontemplation and Contemplation). It would also allow analysis of the pattern of change and detection of differential treatment

effects for different stages and the pattern of the differential effects over time. These types of analyses are essential for refining our research and treatment models.

If an intervention is mismatched to the person's stage of readiness to change, then the person is more likely to resist, drop out or be a treatment failure (DiClemente et al., 1991; Miller & Rollnick, 1991; Prochaska et al., 1992). Many treatment programs are designed to help people ready for action and may be inappropriate for those who are not intrinsically motivated to change or who have much ambivalence. Stage matched interventions have shown promising results. Intervention programs for the majority of smokers in the Precontemplation, Contemplation, and Preparation stages have been developed (Prochaska et al., 1993) over the past 15 years. The most current technology available is used to apply behavioral principles based on the stages of change in a manner that models clinical interventions. An expert system has been used to individualize the interventions to the participant's stage and interact with them around the processes and principles that are necessary for them to progress (Prochaska et al., 2001). The program is designed for an entire population of smokers not just those in the Preparation stage and has produced outcomes of 25% abstinence at 18-month follow-up (Prochaska et al., 1993).

Outcomes alone do not explain why a treatment does or does not work. Questions about treatment effectiveness cannot be completely answered, even with significant outcome results unless process evaluation can be used to support

hypothesized mechanisms of action (DiClemente, Carrol, Connors & Kadden, 1994). We must be concerned with developing effective interventions and rigorous methodologies for testing them and demonstrating the conditions under which they are useful (Mattson & Donovan, 1994). Analysis of stage transitions over time combines outcome measures with process analysis. Recent advances in methodology improve our ability to incorporate stage as an outcome into a process analysis. A recent advancement is Latent Transition Analysis (LTA; Collins, Wuglater, & Rousculp, 1991; Collins, Lanza, Schafer, & Flaherty, 2002), a method of analyzing categorical dynamic latent constructs over time.

Latent Transition Analysis

The current study uses LTA, an extension of latent class theory (Goodman, 1974), to estimate and test stage-sequential models of change. LTA is appropriate for discrete longitudinal data where change, development, or individual growth is of interest. LTA models may include both static and a dynamic part. The dynamic part of LTA models changes over time and can be considered the movement among the stages of change. The variable in LTA associated with the dynamic portion of the model is called latent status. The stages of change involve five latent statuses: Precontemplation (PC), Contemplation (C), Preparation (PR), Action (A), and Maintenance (M). Latent status is measured repeatedly over time and in the current study it is measured five times: at baseline, and 6 months, 12 months, 18 months, and 24 months after baseline. The static part of LTA models does not change over time and is used to divide the sample into groups. The variable in LTA associated

with the static portion of the model is called latent class. Treatment group assignment is the static latent class in this study. The latent class division permits comparison of stage membership and stage transitions between two treatment groups.

LTA models involve five different types of parameters: 1) the gamma parameters (γ), which are estimates of the proportion of the population in each latent class; 2) the delta parameters (δ), which are estimates of the proportion of the population in each latent status at each occasion of measurement, conditional on latent class; 3) the tau parameters (τ) which are the conditional probabilities of transitioning from one latent status to another; 4) the rho parameters (ρ) for the static latent variable, which represent measurement error and are estimates of a particular item response conditional on latent status membership; and 5) the rho parameters (ρ) for the dynamic latent variable, which represent measurement error, that are estimates of a particular item response conditional on latent class membership. The current study includes the first three types of parameters.

The gamma parameters represent the proportion in each latent class and in the current study are the proportion of the population in each of the two treatment groups. The delta parameters are the proportion of the population in each of the five latent statuses conditional on treatment group assignment. The delta parameters reflect the proportion of the population in PC, C, PR, A, and M at each occasion for each treatment group. The tau parameter matrix is the transition probability matrix representing the probabilities of transitioning to each of the

latent statuses, or stages, at each time, conditional on stage at the previous occasion and latent class (treatment group). There is one tau matrix for each latent class (treatment group) and is in our example a 5×5 matrix. When movement among stages can be either forward or backward, there is a full probability matrix. The diagonal elements of the tau matrix represent stability, i.e., the proportion of individuals who remain in the same latent status on both occasions of measurement. The elements above the diagonal represent progression. These values represent the proportion of individuals who move forward to a new latent status on the second occasion. The elements below the diagonal represent regression, i.e., the proportion of individuals who move backward to a previous latent status on the second occasion.

Until recently, LTA used the Estimation Maximization (EM; Dempster, Laird, & Rubin, 1977) algorithm to produce maximum likelihood estimates for latent transition models. The maximum likelihood solution, however, does not provide standard errors. Recent advances in the LTA software (Collins, Schafer, Hyatt, & Flaherty, in preparation; Hyatt, Collins, & Schafer, 1999; Brunner, & Schafer, 1997) now use an Empirical Bayes approach, using data augmentation (DA; Schafer, 1997) for obtaining standard error estimates. Standard error estimates are useful in two ways: they provide a measure of uncertainty for each parameter estimate and they allow for hypothesis testing. Significance tests for differences between parameter estimates are conducted on the DA estimates and standard errors.

Hypothesis testing of LTA parameters can be performed using differences of proportions or relative risk ratios. For differences in proportions, the null hypothesis of no difference is rejected if the confidence interval for the difference does not contain zero. The technical details of conducting hypothesis testing are found in Hyatt, Collins, & Schafer (1999).

Previous studies have applied LTA to stages of change for smoking cessation in the adult population (Martin, Velicer, & Fava, 1996; Velicer, Martin & Collins, 1996). LTA was used to test three alternative models of transitions among the stages of change for smoking cessation (Martin, Velicer, & Fava, 1996). The models assessed movement among the stages for a two-year period. The model that fit the data best indicates that in a six-month period both progression and regression among the stages takes place as well as two-stage progression. Examination of the probability of movement among the stages revealed three findings consistent with the Transtheoretical Model of behavior change. First, movement through the stages is not always linear. Second, the probability of forward movement is greater than backward movement. Third, the probability of moving to adjacent stages was greater than probability of two-stage progression.

The current study replicates previous descriptive findings and extends this program of research in two ways. First, LTA will be applied inferentially to examine differential treatment effects for stage-matched intervention versus control condition for smoking cessation in a sample of adult proactively recruited smokers.

Second, analysis of stage transitions over time will be examined as a process evaluation.

This study provides an empirical example of the application of LTA to the stages of change and smoking cessation among adults. The application of latent transition methodology to the stages of change will be informative on two levels: methodological and theoretical. First, because the stage of change model is well researched and understood, it provides a platform to which the strengths and limitation of the latent transition methodology may be studied. Therefore, one can gauge the usefulness of LTA in contributing unique information to a well-studied phenomenon. Second, the applications to the stages of change will provide a more detailed picture of how people change over time as compared to what is found using traditional data analytic techniques. The study will demonstrate the types of information obtained using LTA and the utility of LTA for examining group differences.

Method

This study is a secondary analysis to data collected in a larger study (Prochaska, 2001). The purpose of the larger study was to test a stage-matched expert system intervention on a representative sample of smokers who were proactively recruited via telephone calls. A two arm randomized control trial was used with four follow-ups over 24 months.

Procedure

A variation of the two-stage Mitofsky-Waksberg random digit-dialing procedure (Lepkowski, 1988; Waksberg, 1978) was used to identify a representative sample of smokers in three distinct geographic areas representing the state of Rhode Island. A total of 32,456 calls were made to identify 14,266 eligible subjects. Of these, 12,109 (84.8%) agreed to complete a brief phone survey. The survey participants included 4,296 smokers (35.5%) and 7,813 nonsmokers. (The procedure over sampled smokers in each household called.) After completing the 20-min phone interview, smokers were invited to participate in the study and asked to provide an address where written materials could be sent. A total of 4,144 agreed to participate and were mailed written materials. No incentives were employed. Between the initial refusal to complete the interview and refusal to participate at the end of the call, 80.0% of the smokers were recruited. See Fava, Velicer, and Prochaska (1995) for a more detailed analysis of the subject recruitment procedure.

Subjects were randomly assigned to an Expert System intervention condition or an Assessment Only control condition. Assignment of smokers to Assessment Only and Expert System conditions followed a 2 to 1 ratio. Those assigned to the Expert System treatment condition ($N = 1,358$) were mailed intervention materials at baseline and at 3 and 6 months. Mailed materials included the baseline feedback report and stage-matched self-help manuals. Smokers in the

Assessment Only group ($N = 2,786$) were proactively assessed at six-month intervals.

At 3 and 6 months, treatment subjects were mailed a progress questionnaire. Approximately 30% of the subjects returned the questionnaire within 2 weeks. Those not responding were surveyed by telephone. Once a survey was completed, an expert system progress report was generated by mail. At 6 months, the proactive assessment subjects were also surveyed using the same dual modality (mail and telephone) procedure. At 12, 18, and 24 months, all continuing participants in both conditions were assessed by mail or telephone survey.

Interventions

The expert system intervention involves a series of three computer reports at the start of treatment and at 3 and 6 months. The two to three page, single-spaced reports were divided into four sections: (a) a description of the person's stage of change, their pros and cons of quitting, and feedback, when necessary about their under-evaluating the pros of quitting and over-evaluating the cons; (b) feedback on their use of up to six change processes which noted how they compared normatively on each process with self-changers who were most successful in progressing to the next stage, and how they compared ipsatively with their previous assessment; (c) a description of tempting situations to smoke, with feedback on how to enhance their self-efficacy in their most tempting situations and, (d) a section on strategies for taking small steps to progress to the next stage, e.g. having smokers in the Contemplation stage delay their first cigarette in the morning for an

extra 30 minutes.

The progress reports also referred participants to sections of stage-matched self-help manuals that were most relevant to their individual progress (Velicer, Rossi, Ruggiero, & Prochaska, 1994). Each manual teaches users about their particular stage of change and the processes they can use to progress to the next stage. Based on their pretest scores, treatment participants were sent the manual matched to their individual stage of change and manuals for all subsequent stages. Participants who took action and relapsed were sent a recycling manual at either the 3 or 6-month follow-up, depending on when they relapsed. Participants who regressed to an earlier stage before quitting were sent the manual that matched their current stage. The reports were mailed immediately upon completion of their telephone survey or receipt of their mailed survey. More details about the expert system and manuals are available elsewhere (Velicer et al., 1993; Velicer et al., 1994).

In the original study, the primary outcomes were point prevalence and prolonged abstinence rates. At 24 months the expert system resulted in 25.6% point prevalence and 12% prolonged abstinence, which were 30% and 56% greater than the control condition. Abstinence rates at each 6-month follow-up were significantly greater in the expert system condition than in the comparison condition with the absolute difference increasing at each follow-up.

Participants

Of the 4,144 smokers, 42.1 % were in the Precontemplation stage, 40.3% in

Contemplation, and 17.6% in Preparation. There were no significant differences between the two treatment groups on gender, age, race, education, income, marital status, years smoking, and number of cigarettes smoked per day. The sample averaged 41 years of age, 56% were female, 54% were married, and 95% were white. The median education level was Grade 12. Compared to other recent samples from the state of Rhode Island, this sample is demographically representative of the population. The sample appears to be very similar to representative national samples, with the exception of the proportions for ethnic and racial subgroups.

Method of Analysis

The analysis was performed using WinLTA (Collins, Lanza, Schafer, & Flaherty, 2002). First, LTA was used to specify a model that best explains movement between the stages over time and to examine transitions between the stages. A good fitting model will have predictions that are close to the actual data. The goodness of fit statistic, G^2 , will be small relative to degrees of freedom for a good fitting model (Graham, Collins, Wugalter, Chung, & Hansen, 1991). G^2 , a likelihood-ratio goodness-of-fit statistic, is approximately distributed as a chi-square where degrees of freedom is equal to the number of response patterns minus the number of estimated parameters minus one. A model building approach was used in model testing where each subsequent model added transition probability parameters to the previous model. Five nested models, similar to models in previous studies (Martin et al., 1996; Evers, Harlow, Redding, & LaForge, 1998),

were compared for goodness of fit using double crossvalidation (Cudeck & Browne, 1983). Double crossvalidation involves identifying a set of plausible models, estimating parameters separately in each half of a randomly split sample, and the computing two fit indices by applying each model as fitted in one half to the opposite half of the sample. The crossvalidation fit indices are examined and the model with the best indices is selected. Figure 1 presents the five models.

Model 1 proposes one stage forward movement. Model 2 proposes one stage forward and backward movement. Model 3 proposes one stage forward and backward movement and two stage forward movement. Model 4 proposes one stage forward and backward movement, two-stage forward movement, and two stage backward movement. Model 5 proposes one stage forward and backward movement, two stage forward and backward movement, and three stage forward movement. Nested models are compared by subtracting the values of G^2 and associated degrees of freedom for the smaller, more restrictive, model from the larger, more general, model.

Second, delta parameter and tau parameter estimates are analyzed descriptively. The delta parameters provide information of how the stage membership (proportion of the population in each stage) changes over time. The tau parameters provide detailed information on the probability of transitioning from one stage to another conditional on treatment group and previous stage. Third, differential treatment effects are examined using data augmentation procedures to

Figure 1

Five alternate nested models

Model 1

Model 2

Model 3

Model 4

Model 5

test a series of planned comparison comparing delta and tau parameter estimates between treatment and control conditions. Because this is the first application of the data augmentation procedures to stage of change data, the difference of proportions between the control and intervention groups on all delta and tau parameters is of interest. Fourth, an application of how LTA data can be examined as a process evaluation is provided.

The LTA routine for incomplete data was used so all cases could be employed at all time points. The procedure is based on computational techniques developed to handle missing data in contingency tables (Schafer, 1997) and is robust when the data are missing completely at random or missing at random (Hyatt & Collins, 1998).

Results

Overall Model Fit

Following the recommendation of Cudeck & Brown (1983) double crossvalidation procedures were used to specify models and compare model fit. The sample was randomly split into two samples, A and B, and parameter values for each of the five models were estimated separately in each half and then fit indices were computed by applying each model as fitted in one half to the opposite half of the sample.

Table 1 displays the G^2 and degrees of freedom results of the double crossvalidation procedure for the five models. The results are presented for half the

Table 1

Results of Crossvalidation on Sample Split Randomly into Samples A and B

		Sample A		Sample B	
		Calibration G^2 on A	Cross- Validation G^2 on B	Calibration G^2 on B	Cross- Validation G^2 on A
Model 1	G^2 df	4654.34 6209	4710.39	4655.17 6209	4711.99
Model 2	G^2 df	3722.33 6183	3904.07	3799.61 6183	3879.70
Model 3	G^2 df	3039.79 6159	3311.12	3182.13 6159	3230.72
Model 4	G^2 df	3009.83 6141	3253.12	3094.73 6141	3180.82
Model 5	G^2 df	2715.49 6129	2945.89	2771.73 6129	2906.08

Note. Model 1 proposes one stage forward movement. Model 2 proposes one stage forward and backward movement. Model 3 proposes one stage forward and backward movement and two stage forward movement. Model 4 proposes one stage forward and backward movement, two-stage forward movement, and two stage backward movement. Model 5 proposes one stage forward and backward movement, two stage forward and backward movement, and three stage forward movement.

sample, labeled Sample A, and then for the other half of the sample, labeled Sample B. Results of the initial model estimation on each half of the sample are in the columns labeled Calibration G^2 . Results of each model as fitted in one half of the sample as applied to the opposite half are presented in the columns labeled Crossvalidation G^2 . Overall model fit for the five models is carried out by comparing model fit statistics using G^2 difference tests. G^2 difference tests are presented in Table 2. A nonsignificant value of G^2 difference suggests the overall fits of the two models are comparable. A significant result supports retaining the parameters added by the larger, more general, model. Assuming the G^2 difference is distributed as chi-square, the more restrictive, smaller, model represents a significant decrement in model fit compared with the more general model.

A significant difference was found between Model 4 and Model 5, which typically would suggest retaining the larger model (in this case Model 5). However, Model 4 was selected over Model 5 as the best fitting model despite the significant G^2 difference test between the two models for several reasons. First, examination of the residuals indicated that the transitions added to Model 5 (PC to A and C to M) were represented in a very small proportion of the sample (1% from baseline to 6 months, .6% from 6 to 12 months, .8% from 12 to 18 months, and 1.2% from 18 to 24 months). Second, the purpose of model specification is to parsimoniously explain observations, using the least number of parameters as possible. The additional transitions of Model 5 account for a small proportion of the observed data and therefore are not theoretically meaningful despite being statistically

Table 2

Results of G^2 Difference Tests Comparing Nested Models

	Sample A		Sample B	
	G^2 difference	df	G^2 difference	df
Model 1-2	806.32	26*	832.29	26*
Model 2-3	592.95	24*	649.18	24*
Model 3-4	58.00	18*	49.90	18*
Model 4-5	307.23	12*	274.74	12*

* $p < .001$

significant. Third, the limitations of the G^2 fit index warrant a closer examination of the results. When the absolute magnitude of the change in the parameter estimate is small as is true in this case, then significance may be due more to large sample size than to the size of the effect (Kline, 1998). And as noted earlier LTA models tend to involve large contingency tables. Under these conditions the G^2 is usually not distributed as a chi-square so overall hypothesis testing can be done in only an approximate way (Collins, Fidler, Wugalter, & Long, 1993).

Invariance of the models was tested by running each of the models on each treatment group independently. Model fit was approximately the same within each group.

Gamma Parameter Estimates (Probabilities of Latent Class Membership)

The gamma parameters represent the proportion of the population in each of the two latent classes or in this case treatment groups. Thirty-three percent (95% CI .314-.342) of the population was in the intervention group and 67% (95%CI .658-.686) was in the control group. These proportions reflect the 2 to 1 ratio used for random assignment in the primary study.

Delta Parameter Estimates (Probabilities of Latent Status Membership)

The delta parameters are the proportion of the population in each of the latent statuses (e.g. stages) at each time conditional on latent class (e.g. treatment assignment). The delta parameter estimates and confidence intervals are presented in Table 3.

Table 3

Estimates and 95% CI of Delta (δ) Parameters, Probabilities of Latent Status Membership

	Baseline	6 Months	12 Months	18 Months	24 Months
<u>Precontemplation</u>					
Intervention	.414 [.410-.418]	.424 [.418-.429]	.385 [.372-.397]	.361 [.352-.371]	.371 [.364-.377]
Control	.420 [.417-.423]	.458 [.456-.460]	.431 [.426-.435]	.409 [.404-.415]	.410 [.403-.413]
<u>Contemplation</u>					
Intervention	.424 [.422-.426]	.344 [.338-.351]	.320 [.309-.330]	.299 [.287-.312]	.255 [.244-.267]
Control	.404 [.402-.406]	.366 [.363-.370]	.322 [.317-.328]	.314 [.310-.318]	.279 [.274-.285]
<u>Preparation</u>					
Intervention	.160 [.157-.163]	.152 [.149-.156]	.146 [.141-.151]	.142 [.134-.151]	.133 [.128-.139]
Control	.174 [.172-.177]	.119 [.116-.122]	.120 [.116-.125]	.130 [.126-.135]	.137 [.133-.141]
<u>Action</u>					
Intervention	.0	.078 [.074-.082]	.111 [.105-.117]	.115 [.109-.119]	.115 [.109-.118]
Control	.0	.056 [.053-.059]	.108 [.106-.109]	.087 [.085-.090]	.092 [.088-.095]
<u>Maintenance</u>					
Intervention	.0	.0	.037 [.036-.039]	.081 [.077-.085]	.126 [.119-.133]
Control	.0	.0	.018 [.017-.019]	.057 [.056-.059]	.083 [.079-.086]

Note. A value of .0 indicates that the parameter was fixed at zero.

It was hypothesized that at each follow-up the intervention group would have lower probabilities of being in the Precontemplation and Contemplation stages of change and have higher probabilities of being in the Preparation, Action and Maintenance stages of change compared to the control group. This hypothesis was supported.

At each follow-up the intervention group had a lower proportion in Precontemplation (.424 at 6 months, .385 at 12-months, .361 at 18 months and .371 at 24 months) compared to the control group (.458 at 6 months, .431 at 12-months, .409 at 18 months and .410 at 24 months). At each follow-up the intervention group has a lower proportion in Contemplation (.344 at 6 months, .320 at 12-months, .299 at 18 months and .255 at 24 months) compared to the control group (.366 at 6 months, .322 at 12-months, .314 at 18 months and .279 at 24 months).

The intervention group also had a higher proportion in Preparation, Action and Maintenance compared to the control group. The intervention group has a higher proportion in Preparation (.152 at 6 months, .146 at 12-months, and .142 at 18 months) compared to the control group (.119 at 6 months, .120 at 12-months, and .130 at 18 months) except at 24 months where the intervention group (.133) is approximately the same as the control group (.137). At each follow-up the intervention group has a higher proportion in Action (.078 at 6 months, .111 at 12-months, .115 at 18 months and .115 at 24 months) compared to the control group (.056 at 6 months, .108 at 12-months, .087 at 18 months and .092 at 24 months). At each follow-up the intervention group has a higher proportion in Maintenance

(.037 at 12-months, .081 at 18 months and .126 at 24 months) compared to the control group (.018 at 12 months, .057 at 18-months, and .083 at 24 months).

It was also hypothesized that the proportion in Precontemplation, Contemplation, and Preparation would decrease over time and that the membership in Action and Maintenance would increase over time. The results for the intervention group support this hypothesis. The proportion in Precontemplation in the intervention group decreases over time except at 6 and 24 months (.414 at baseline, .424 at 6 months, .385 at 12-months, .361 at 18 months and .371 at 24 months). The proportion in Contemplation in the intervention group decreases over time (.424 at baseline, .344 at 6 months, .320 at 12-months, .299 at 18 months and .255 at 24 months). The proportion in Preparation in the intervention group decreases over time (.160 at baseline, .152 at 6 months, .146 at 12-months, .142 at 18 months, and .133 at 24 months). The proportion in Action in the intervention group increases over time (.078 at 6 months, .111 at 12-months, .115 at 18 months and .115 at 24 months) and the proportion in Maintenance increases over time (.037 at 12-months, .081 at 18 months and .126 at 24 months).

The results for the control group show mixed support for the hypothesis. The proportion in Precontemplation in the control group decreases over time except at 6 and 24 months (.420 at baseline, .458 at 6 months, .431 at 12-months, .409 at 18 months and .410 at 24 months). The proportion in Contemplation in the control group decreases over time (.404 at baseline, .366 at 6 months, .322 at 12-months, .314 at 18 months and .279 at 24 months). The proportion in Preparation in the

control group increases over time (.174 at baseline, .119 at 6 months, .120 at 12-months,.130 at 18 months, and .137 at 24 months) except from 6 to 12 months where it remains the same. The proportion in Action in the control group increases from 6 to 12 months (.056 at 6 months, .108 at 12-months) and then decreases at 18 months (.087) and 24 months (.092). The proportion in Maintenance in the control group increases over time (.018 at 12 months, .057 at 18-months, and .083 at 24 months).

Some interesting group differences have emerged. In a later section hypothesis tests will be conducted to see if the differences are statistically significant.

Tau Parameter Estimates (Probabilities of Latent Status Transitions)

A specific interest of this study is the difference between the intervention group and control group in overall transitions among the stages of change. The tau parameters represent the conditional probability of transitioning to a particular stage of change given the previous stage of change and the treatment group assignment. The tau parameter estimates and the associated 95% confidence intervals are presented in matrix form in Table 4. Figure 2 displays the tau parameter estimates graphically. Examination of the tau parameter matrices in Table 4 provides very detailed information regarding the probability of transitioning from one stage of change to another (conditional on previous stage of change and treatment group). The cells above the diagonal indicate advancement in stage, or progression. The cells along the diagonal indicate no change in stage,

Table 4

Estimates and 95% CI of Tau (τ) Parameters, Probabilities of Latent Status Transitions

Baseline Stage of Change	6 Month Stage of Change				
	PC	C	PR	A	M
<u>Intervention Group</u>					
Precontem- plation	.761 [.703-.811]	.192 [.152-.239]	.047 [.024-.087]	.0	.0
Contem- plation	.219 [.177-.267]	.503 [.452-.553]	.161 [.126-.203]	.117 [.083-.161]	.0
Preparation	.098 [.051-.173]	.319 [.250-.397]	.402 [.327-.482]	.178 [.126-.245]	.002 [.000-.035]
Action	.0	.0	.0	1.00	.0
Mainte- nance	.0	.0	.0	.0	1.00
<u>Control Group</u>					
Precontem- plation	.790 [.753-.823]	.184 [.156-.216]	.026 [.016-.042]	.0	.0
Contem- plation	.279 [.252-.308]	.510 [.475-.545]	.122 [.101-.146]	.089 [.067-.117]	.0
Preparation	.073 [.049-.107]	.472 [.405-.541]	.338 [.286-.395]	.115 [.077-.167]	.001 [.000-.016]
Action	.0	.0	.0	1.000	.0
Mainte- nance	.0	.0	.0	.0	1.000

Table 4 (continued)

6 Month Stage of Change	12 Month Stage of Change				
	PC	C	PR	A	M
<u>Intervention Group</u>					
Precontem- plation	.746 [.676-.807]	.219 [.168-.280]	.034 [.013-.081]	.0	.0
Contem- plation	.178 [.131-.236]	.578 [.454-.581]	.167 [.125-.218]	.138 [.103-.181]	.0
Preparation	.046 [.002-.355]	.305 [.217-.408]	.415 [.331-.503]	.230 [.161-.316]	.004 [.000-.054]
Action	.0	.025 [.001-.227]	.140 [.060-.279]	.361 [.240-.501]	.474 [.350-.602]
Mainte- nance	.0	.0	.0	.0	1.00
<u>Control Group</u>					
Precontem- plation	.780 [.746-.811]	.199 [.169-.233]	.021 [.010-.040]	.0	.0
Contem- plation	.195 [.169-.224]	.575 [.476-.553]	.147 [.120-.180]	.143 [.116-.174]	.0
Preparation	.019 [.003-.090]	.294 [.240-.354]	.442 [.366-.519]	.244 [.179-.321]	.002 [.000-.026]
Action	.0	.135 [.057-.271]	.078 [.028-.183]	.465 [.347-.587]	.321 [.237-.418]
Mainte- nance	.0	.0	.0	.0	1.000

Table 4 (continued)

12 Month Stage of Change	18 Month Stage of Change				
	PC	C	PR	A	M
<u>Intervention Group</u>					
Precontem- plation	.780 [.703-.843]	.211 [.153-.281]	.009 [.000-.164]	.0	.0
Contem- plation	.187 [.127-.263]	.547 [.479-.614]	.154 [.108-.212]	.113 [.070-.172]	.0
Preparation	.012 [.000-.124]	.262 [.162-.389]	.505 [.362-.647]	.218 [.134-.328]	.003 [.000-.047]
Action	.0	.047 [.006-.209]	.130 [.061-.244]	.381 [.275-.500]	.442 [.325-.565]
Mainte- nance	.0	.0	.047 [.002-.374]	.133 [.008-.628]	.820 [.447-.972]
<u>Control Group</u>					
Precontem- plation	.786 [.748-.821]	.179 [.146-.217]	.035 [.020-.058]	.0	.0
Contem- plation	.216 [.182-.254]	.543 [.499-.586]	.136 [.103-.176]	.105 [.082-.134]	.0
Preparation	.007 [.000-.095]	.416 [.336-.500]	.441 [.365-.519]	.134 [.094-.186]	.003 [.000-.033]
Action	.0	.113 [.058-.202]	.170 [.116-.239]	.327 [.244-.421]	.390 [.310-.476]
Mainte- Nance	.0	.0	.017 [.001-.200]	.138 [.040-.349]	.846 [.668-.940]

Table 4 (continued)

18 Month Stage of Change	24 Month Stage of Change				
	PC	C	PR	A	M
<u>Intervention Group</u>					
Precontem- Plation	.829 [.752-.887]	.164 [.109-.234]	.008 [.000-.080]	.0	.0
Contem- Plation	.224 [.168-.291]	.496 [.388-.604]	.155 [.110-.213]	.125 [.065-.217]	.0
Preparation	.029 [.004-.131]	.297 [.193-.424]	.505 [.375-.635]	.165 [.086-.284]	.004 [.000-.049]
Action	.0	.042 [.001-.405]	.085 [.029-.202]	.332 [.197-.496]	.541 [.376-.698]
Mainte- nance	.0	.0	.036 [.001-.367]	.184 [.104-.301]	.779 [.626-.886]
<u>Control Group</u>					
Precontem- plation	.824 [.782-.860]	.155 [.119-.197]	.021 [.007-.057]	.0	.0
Contem- plation	.201 [.168-.239]	.534 [.491-.576]	.155 [.122-.194]	.110 [.084-.143]	.0
Preparation	.059 [.011-.221]	.351 [.273-.437]	.447 [.362-.533]	.141 [.098-.196]	.002 [.000-.032]
Action	.0	.028 [.000-.386]	.159 [.091-.257]	.351 [.244-.473]	.462 [.355-.572]
Mainte- nance	.0	.0	.131 [.071-.226]	.142 [.072-.253]	.726 [.574-.843]

Note. A value of .0 indicates that the parameter was fixed at zero.

Figure 2

Tau parameter estimates. Intervention group estimates are marked in italics type and control group estimates are in parentheses.

Figured 2 continued

18 Months to 24 Months

or stability. The cells below the diagonal indicate returning to a previous stage, or regression.

Several general observations can be made about the pattern of the transition probabilities. First, the probability of transition to adjacent stages was greater than nonadjacent stages. Although two-stage progression or regression within a six-month period is possible, it is more probable to transition to the next stage. The probability of progression from Precontemplation to Preparation is .008 at its lowest (for the intervention group at 18 months) and .047 at its highest (for the intervention group at baseline). The probability of progression from Contemplation to Action is .089 at its lowest (for the control group at baseline) and .143 at its highest (for the control group at 6 months). The probability of progression from Preparation to Maintenance is less than .01 at all time points for both groups. The probability of regression from Action to Contemplation is .025 at its lowest (for the intervention group at 6 months) and .135 at its highest (for the control group at 18 months). The probability of regression from Maintenance to Preparation is .017 at its lowest (for the control group at 12 months) and .131 at its highest (for the control group at 18 months).

Second, for three stages, Precontemplation, Contemplation, and Maintenance, the probability of remaining at the same stage from one time point to the next was greater than the probability of transitioning to all other stages combined. The probability of remaining in Precontemplation for the intervention group was .790 at 6 months, .780 at 12 months, .786 at 18 months, and .824 at 24

months. The probability of remaining in Precontemplation for the intervention group was .761 at 6 months, .746 at 12 months, .780 at 18 months, and .829 at 24 months. The probability of remaining in Contemplation for the control group was .503 at 6 months, .578 at 12 months, .547 at 18 months, and .496 at 24 months. The probability of remaining in Contemplation for the control group was .510 at 6 months, .575 at 12 months, .543 at 18 months, and .534 at 24 months. The probability of remaining in Maintenance for the intervention group was .820 at 18 months and .779 at 24 months. The probability of remaining in Maintenance for the control group was .846 at 18 months and .726 at 24 months.

Third, the probability of transitioning is the highest for the Action stage. The probability of remaining in Action for the intervention group was .361 at 12 months, .381 at 18 months, and .332 at 24 months. The probability of remaining in Action for the control group was .465 at 12 months, .327 at 18 months, and .351 at 24 months.

It was hypothesized that the probability of progression would be greater than regression for any stage across both the intervention and control groups. The probability of progression is calculated by summing transition probabilities above the diagonal element for each stage. The probability of regression is calculated by summing the transition probabilities below the diagonal element for each stage. This hypothesis was supported in both the intervention group and the control group except for the Preparation stage that consistently had greater regression than progression. For the intervention group the probability of progression was greater

than regression for Contemplation from baseline to 6 months (.278 vs. .219), 6 months to 12 months (.305 vs. .178), 12 months to 18 months (.267 vs. .187), and 18 months to 24 months (.280 vs. .224). For the control group the probability of progression was greater than regression for Contemplation from 6 months to 12 months (.290 vs. .195), 12 months to 18 months (.241 vs. .216), and 18 months to 24 months (.265 vs. .201), but not from baseline to 6 months (.211 vs. .279). For the intervention group the probability of progression was greater than regression for Action from 6 months to 12 months (.474 vs. .165), 12 months to 18 months (.442 vs. .177), and 18 months to 24 months (.541 vs. .127). For the control group the probability of progression was greater than regression for Action from 6 months to 12 months (.321 vs. .213), 12 months to 18 months (.390 vs. .283), and 18 months to 24 months (.462 vs. .187). For the intervention group the probability of regression was greater than progression for Preparation from 6 months to 12 months (.234 vs. .351), 12 months to 18 months (.221 vs. .274), and 18 months to 24 months (.169 vs. .326), but not from baseline to 6 months (.180 vs. .117). For the control the probability of regression was greater than progression for Preparation group from baseline to 6 months (.116 vs. .545), 6 months to 12 months (.246 vs. .313), 12 months to 18 months (.137 vs. .423), and 18 months to 24 months (.143 vs. .410).

It was hypothesized that intervention group would experience less regression and more progression among the stages compared to the control group. This hypothesis was supported. For Precontemplation, the probability of

progressing is higher for the intervention group (.239 from baseline to 6 months, .253 from 6 to 12 months, .221 from 12 to 18 months, .172 from 18 to 24 months) than the control group (.210 from baseline to 6 months, .220 from 6 to 12 months, .214 from 12 to 18 months, .176 from 18 to 24 months) except from 18 to 24 months where the probabilities are about the same.

For Contemplation, the probability of progressing is higher for the intervention group (.278 from baseline to 6 months, .305 from 6 to 12 months, .267 from 12 to 18 months, .280 from 18 to 24 months) than the control group (.211 from baseline to 6 months, .290 from 6 to 12 months, .241 from 12 to 18 months, .265 from 18 to 24 months) and the probability of regressing is lower in the intervention group (.219 from baseline to 6 months, .178 from 6 to 12 months, .187 from 12 to 18 months, .224 from 18 to 24 months) than the control group (.279 from baseline to 6 months, .195 from 6 to 12 months, .216 from 12 to 18 months, .201 from 18 to 24 months).

For Preparation, the probability of progressing is higher for the intervention group (.180 from baseline to 6 months, .221 from 12 to 18 months, .169 from 18 to 24 months) than the control group (.116 from baseline to 6 months, .137 from 12 to 18 months, .143 from 18 to 24 months) except from 6 to 12 months where the probability of progressing is lower in the intervention group (.234) than the control group (.246). The probability of regressing is lower in the intervention group (.219 from baseline to 6 months, .274 from 12 to 18 months, .326 from 18 to 24 months) than the control group (.545 from baseline to 6 months, .423 from 12 to 18 months,

.410 from 18 to 24 months) except from 6 to 12 months where the probability of regressing is higher in the intervention group (.351) than the control group (.313).

For Action, the probability of progressing is higher for the intervention group (.474 from 6 to 12 months, .442 from 12 to 18 months, .545 from 18 to 24 months) than the control group (.321 from 6 to 12 months, .390 from 12 to 18 months, .463 from 18 to 24 months) and the probability of regressing is lower in the intervention group (.165 from 6 to 12 months, .177 from 12 to 18 months, .127 from 18 to 24 months) than the control group (.213 from 6 to 12 months, .283 from 12 to 18 months, .187 from 18 to 24 months).

For Maintenance, the probability of regression is higher for the intervention group from 12 to 18 months (.180) compared to the control group (.155) and is lower for the intervention group from 18 to 24 months (.220) compared to the control group (.273).

Overall, there is a strong pattern in the tau parameter values that indicate the intervention has better outcomes compared with the control group.

Results of Tests of Hypotheses

Tests of significance were conducted to examine hypotheses about group differences in delta parameters and the tau parameters. Results from these tests based on the differences of proportions are presented. For differences of proportion, the null hypothesis of no difference is rejected if the confidence interval for the difference does not contain zero.

Several tests of delta parameters reach statistical significance as shown in

Table 5. At 6 months, those in the intervention group are significantly more likely to be in Preparation ($\delta=.152$) compared with the control group ($\delta=.119$) and are also more likely to be in Action ($\delta=.115$) compared with the control group ($\delta=.056$). At 12 months, those in the intervention group are significantly more likely to be in Maintenance ($\delta=.037$) compared with the control group ($\delta=.018$). At 18 months, those in the intervention group are significantly less likely to be in Precontemplation ($\delta=.361$) compared with the control group ($\delta=.409$) and are also more likely to be in Action ($\delta=.078$) and Maintenance ($\delta=.081$) compared with the control group ($\delta=.087$ for Action and $\delta=.057$ for Maintenance). At 24 months, those in the intervention group are significantly more likely to be in Maintenance ($\delta=.126$) compared with the control group ($\delta=.083$).

Several tests of the tau parameters reached significance. Table 6 presents the differences of proportions and 95% CI for the tau parameters. Two differences in proportions are significant from baseline to 6 months. The probability of regressing from Contemplation to Precontemplation is higher for the control group ($\tau=.279$) than for the intervention group ($\tau=.219$). The probability of regressing from Preparation to Contemplation is higher for the control group ($\tau=.472$) than for the intervention group ($\tau=.319$). From 6 months to 12 months the probability of regressing from Action to Contemplation is higher for the control group ($\tau=.135$) than for the intervention group ($\tau=.025$). From 12 months to 18 months the probability of progressing from Precontemplation to Preparation is higher for the control group ($\tau=.035$) than for the intervention group ($\tau=.009$).

Table 5

Hypothesis Testing: Difference of Proportions and 95% CI for Delta (δ) Parameters

	Baseline	6 months	12 months	18 months	24 months
Precontem- plation	0.06 [-.027-.039]	.034 [-.002-.069]	.046 [-.003-.096]	.048* [.004-.092]	.038 [-.001-.077]
Contem- plation	.020 [-.014-.053]	.022 [-.018-.062]	.003 [-.041-.046]	.015 [-.026-.046]	.024 [-.019-.068]
Preparation	.015 [-.012-.041]	.033* [.007-.059]	.025 [-.007-.058]	.012 [-.017-.042]	.003 [-.023-.030]
Action	---	.022* [.001-.043]	.003 [-.022-.029]	.027* [.001-.054]	.022 [-.004-.048]
Mainte- nance	---	---	.020* [.006-.033]	.023* [.003-.043]	.043* [.012-.074]

* $p < .05$

Table 6

Hypothesis Testing: Differences of Proportions and 95% CI for Tau (τ) Parameters

Baseline Stage of Change	6 Month Stage of Change				
	PC	C	PR	A	M
Precontem- plation	.029 [-.026-.083]	.008 [-.034-.050]	.021 [-.012-.053]	---	---
Contem- plation	.061* [.007-.114]	.007 [-.052-.065]	.039 [-.003-.082]	.028 [-.012-.067]	---
Preparation	.024 [-.036-.084]	.353* [.271-.436]	.066 [-.034-.166]	.063 [-.017-.144]	.001 [.000-.025]
6 Month Stage of Change	12 Month Stage of Change				
	PC	C	PR	A	M
Precontem- plation	.034 [-.039-.106]	.020 [-.039-.080]	.013 [-.011-.038]	---	---
Contem- plation	.017 [-.037-.071]	.003 [-.063-.069]	.019 [-.037-.075]	.005 [-.038-.048]	---
Preparation	.027 [-.034-.088]	.011 [-.085-.108]	.026 [-.081-.133]	.014 [-.076-.105]	.002 [-.010-.014]
Action	---	.110* [.006-.214]	.059 [-.056-.174]	.105 [-.091-.300]	.156 [-.011-.323]

Table 6 (continued)

12 Month Stage of Change	18 Month Stage of Change				
	PC	C	PR	A	M
Precontem- plation	.006 [-.056-.068]	.031 [-.031-.093]	.025* [.004-.047]	---	---
Contem- plation	.029 [-.042-.102]	.005 [-.061-.072]	.018 [-.030-.065]	.007 [-.044-.058]	---
Preparation	.004 [-.022-.030]	.155 [.005-.305]	.067 [-.073-.206]	.082 [-.024-.188]	.002 [-.009-.014]
Action	---	.068 [-.013-.149]	.041 [-.051-.134]	.056 [-.073-.185]	.053 [-.067-.173]
Mainte- nance	---	---	.021 [-.069-.110]	.007 [-.237-.251]	.028 [-.220-.276]
18 Month Stage of Change	24 Month Stage of Change				
	PC	C	PR	A	M
Precontem- plation	.005 [-.051-.061]	.008 [-.041-.058]	.013 [-.010-.037]	---	---
Contem- plation	.023 [-.039-.085]	.037 [-.066-.140]	.000 [-.051-.051]	.015 [-.053-.083]	---
Preparation	.032 [-.025-.088]	.053 [-.063-.169]	.061 [-.053-.176]	.022 [-.074-.117]	.002 [-.009-.014]
Action	---	.013 [-.068-.094]	.076 [-.039-.190]	.019 [-.125-.162]	.081 [-.118-.280]
Mainte- nance	---	---	.094 [-.008-.197]	.039 [-.076-.154]	.056 [-.112-.224]

*p<.05

Process Evaluation

The purpose of the process evaluation is to identify when and what stages of change the intervention is most effective by examining the delta and tau parameters over time. The delta parameters represent the growth and decline of stage membership over time. What is shown in the pattern of delta parameters is that the intervention group consistently reduces membership in the early stages (Precontemplation, Contemplation, and Preparation) and increases membership in the late stages (Action and Maintenance). Consistently the intervention group has lower proportions in the early stages and higher proportions in the late stages compared with the control group. Not only is the stage membership in the early stages lower for the intervention group, it continues to decline over time and the membership in the late stages higher for the intervention group it continues to grow over time.

Examination of the pattern of tau parameter values over time also provides valuable information about when and for which stages of change the intervention is most effective. The tau parameters are evaluated *between groups* and *over time*. A favorable *between groups* outcome for the intervention group is marked by higher probabilities of progressing one or two stages compared to the control group. It is likely that if there is higher probability of progressing within the stages the probability of regressing back one or two stages is lower. From baseline to 6 months the intervention group outperforms the control group for all stages. From 6 months to 12 months the intervention group continues to outperform the control

group with the exception of the Preparation stage where there is more regression to Contemplation and Precontemplation and less progression to Action. From 12 months to 24 months the intervention group outperforms the control group with the exception of the Maintenance stage that has more regression to Preparation and less remaining in Maintenance.

A favorable outcome for the intervention group *over time* is marked by the transition probabilities decreasing for the regression parameters and increasing for the progression parameters. The favorable outcome effects for the Precontemplation and Contemplation stages appear to decline by 18 months. From 12 to 18 months and 18 to 24 months the probability of remaining in Precontemplation or Contemplation increases and the probability of progressing decreases. The favorable outcome effects for the Preparation stage begin to decline by 12 months. From 12 to 18 months and 18 to 24 months the probability of progressing to Action decrease and from 18 to 24 months the probability of regressing to Contemplation or Precontemplation increases. The Action stage outcomes are better for the 18 to 24 month transitions with increased progression and less regression indicating, perhaps that the effects seen in the early stages at earlier time points are continuing with the late stages at the later time points.

The delta parameter and tau parameter information taken together provide another level of information than either of the parameters alone. The consistency of the delta parameter results is remarkable. The membership in the early stages is lower and continues to decline and the membership in the late stages is higher and

continues to increase for the intervention group compared to the control group. Therefore the transition probabilities (tau parameter) for the early stages are applicable to a declining membership and the transition probabilities for the late stages are applicable to growing membership. In other words, the denominator for the transition probability, the proportion in a particular stage at a particular time, is decreasing for the early stages and increasing for the later stages in the intervention group. Although the effects of the intervention are strongest for the early stages but decline over time there is less of the population in the early stages 18 and 24 months after the intervention.

Discussion

The results of this study provide information about latent transition methodology and the application of this methodology to the stages of change for smoking cessation. The study examined model specification, the pattern of parameter values, statistical tests for treatment group differences, and the application of LTA as a process analysis. The type of information obtained using LTA and the utility of LTA for examining group differences was demonstrated.

Examination of the parameter estimates generated using LTA demonstrates a strong pattern of results. The delta estimates, representing the proportion of the population in each stage at each time point conditional on treatment group, differed between the intervention group and control group. The delta parameters show that the intervention group has lower proportions in Precontemplation and Contemplation and higher proportions in Preparation, Action, and Maintenance

compared to the control group. This suggests that that the expert system intervention is effective at helping people to make a cessation attempt and in some instances maintain the quit. A greater number of subjects were engaged in attempts to quit smoking in the intervention group; hence the greater increase in Preparation and Action stage membership.

The pattern of the delta parameter values over time also differed between the two treatment groups. The two groups had noticeable membership differences in Preparation and Action. These results suggest that the intervention is particularly effective in moving people into the later stages of change. Hypothesis tests comparing delta parameters for each treatment group indicate similar results to the descriptive analyses.

The tau parameter pattern indicates a strong intervention effect especially for the early stages at the earliest follow-up periods. There is less regression to an earlier stage and more progression to a later stage in the intervention group. The magnitude of the effect for the early stages decreases over time suggesting that the intervention is beneficial closer to when it is administered. In the case of this study the intervention was administered at baseline, three months, and six months so the effects are larger for the early stages at six and twelve months. These results would appear to contrast the results of Prochaska et al. (2001) which found the treatment effects to increase at each follow-up, however the results of the late stages show the intervention effects increasing over time.

Although movement between the stages is very dynamic, results presented here indicate that smokers and former smokers are more likely to transition to the nearest stage. Two-stage progression or regression is less probable than moving to adjacent stages. This observation has implication for intervention design. It had previously been suggested that targeting stage-matched interventions at helping smokers progress one stage would be beneficial to smokers.

A model building approach was used in model testing where each subsequent model added transition probability parameters to the previous model. The statistical test comparing five nested models, G^2 difference test, failed to retain the null hypothesis of no differences between any two models. The model that specified two-stage forward and backward movement, Model 4, was selected as the best fitting model. From a purely statistical approach, Model 5 provided the best fit to the data. This is particularly interesting after examination of the residuals that demonstrated that the two transition probabilities added by Model 5 accounted for a very small portion of the observed data. This causes one to consider how theoretically meaningful these added parameters are to explaining transitions among the stages of change for smoking. The absolute magnitude of the change in the two added parameters when they were freely estimated was very low and therefore the significance may be due more to the sample size than to the size of the effect (Kline, 1998; Hu & Bentler, 1995). The growing dissatisfaction with the chi-square goodness-of-fit test has led to the generation of a growing number of adjunct fit indexes within SEM (Hoyle, 1995). It is likely that a similar trend will develop

within latent transition methodology. Despite the weakness of the goodness-of-fit test the information provided by latent transition methodology is quite valuable as demonstrated in the current study.

The data augmentation procedure for testing treatment effects did not appear to be a very sensitive test. The transition probability estimates provide a detailed look at movement among the stages of change conditional on previous stage and treatment group. This level of specificity, however, obscures the cumulative effect that may exist in two ways. First, typical point prevalence combines the Precontemplation, Contemplation, and Preparation stages and compares this proportion to the proportion in Action and Maintenance combined. The difference tested with a point prevalence estimate will be larger than the conditional proportions being compared within LTA. Second, point prevalence examines outcome at only one follow-up period. LTA results provided a detailed picture at each of several follow-up periods. Therefore, the cumulative effect seen with point prevalence is divided up among the four follow-up periods. The original study was powered to detect treatment effects in a certain range of potential outcomes, specifically for the proportion of subjects moving into the Action and Maintenance stages. The proportions of the transition probabilities differ from those for which the study was powered to detect, therefore, the test for treatment differences within LTA lacks sufficient power.

This study has served two broad purposes. First, it has demonstrated the utility of latent transition methodology for the study of change. Several strengths

of the method have been demonstrated: estimation of latent status membership, estimation of latent transition probabilities, and the utility of using LTA as a process analysis. Several limitations of the method have been demonstrated: testing alternate models, the potential obscuring of cumulative treatment effects found with traditional methods, and the lack of sensitivity of the data augmentation procedures for testing group differences. Second, this study has demonstrated the utility of employing stage of change as an outcome measure. Stage membership is sensitive to change for all smokers, not just those achieving Action criteria.

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Chapter 3

Evaluating an Expert System Intervention for Smoking Cessation in a Managed Care Setting

New research paradigms need to have us rethink established truths and methodologies and to not generalize from one set of trial conditions to a very different set of conditions. Shifting paradigms for population-based trials is essential for science to progress (Prochaska, Velicer, Fava, Rossi, & Tsoh, 2001a). Researchers must rethink basic research methods including recruitment approach, definitions of meaningful outcomes, appropriateness of interventions, and the method of analysis for population-based trials. Decisions in one of these areas would impact decisions in the other areas.

The most common approach for recruitment for clinical trials has been a reactive approach where subjects are informed of the availability of an intervention program and must contact the program to participate. Reactive recruitment results in low participation rates, typically 1-5% (Schmid, Jeffrey, & Heelerstedt, 1989). A proactive recruitment approach contacts the subjects directly and offers the services to them. Proactive recruitment results in higher participation rates. The interventions that have the highest efficacy for smoking cessation also have the lowest participation rates. Conversely, the clinical trials with the highest participation rates also have the lowest abstinence rates. Both of these programs result in low impact (Velicer & DiClemente, 1993, Velicer & Prochaska, 1999). What the field needs are interventions that can maximize participation rates without

sacrificing abstinence rates (Prochaska et al., 2001a). From the stage of change perspective both these programs have severe limitations in that they are based on an action paradigm where behavior is viewed as dramatic and discrete movement from smoking to nonsmoking (Prochaska et al., 2001a). Prior research demonstrates that at most 20% of smokers plan to quit in the next month and have tried to quit in the past year (Velicer, Fava, Prochaska, Abrams, Emmons, & Pierce, 1995).

In retrospective, cross-sectional, and longitudinal studies of how people quit smoking on their own, evidence indicates that smokers move through a series of stages of change in their attempts to quit smoking (DiClemente & Prochaska, 1982; Prochaska & DiClemente, 1983; Prochaska, DiClemente, Velicer, Ginpil, & Norcross, 1985). A smoker is at any one time in one of five stages of change with respect to quitting smoking: Precontemplation (not thinking about quitting smoking in the next 6 months), Contemplation (seriously thinking about quitting smoking in the next 6 months), Preparation (seriously thinking about quitting smoking in the next month and have made an attempt to quit smoking in the past year), Action (making overt changes to stop smoking and lasts 0-6 months), and Maintenance (has successfully quit smoking for at least 6 months) (Prochaska, DiClemente, & Norcross, 1992; DiClemente, Prochaska, Fairhurst, Velicer, Velasquez, & Rossi, 1991). Longitudinally, people often do not progress steadily through these stages; some stay at one stage while others relapse and cycle back.

The argument for measuring outcome for behavior change from a stage perspective rather than a single manifest variable perspective can be seen in the area of smoking cessation (Velicer, Prochaska, Rossi, & Snow, 1992). The three self-report measures most widely employed for smoking cessation are point prevalence, continuous abstinence, and prolonged abstinence. These criterion measures have cursory face validity but suffer from some severe limitations including lack of precise definitions, poor statistical power, and lack of meaningfulness for some aspects of the problem. The most widely employed measures of smoking outcome are insensitive to change for 80% to 95% of smokers.

Traditional methods of examining these outcomes over time may produce results that are misleading. It is unlikely that those in early stages will reach any of the action paradigm criterion behaviors described above and remain abstinent in a short time frame, but effective interventions with early stage smokers will result in changes in point prevalence in an extended follow-up, such as 18 or 24 months post-intervention, (Prochaska, DiClemente, Velicer, & Rossi, 1993). This is particularly important in smoking research where participants may make some changes during each follow-up period, but not enough change to be considered abstinent. Interventions must facilitate four transitions: 1) Precontemplation to Contemplation, 2) Contemplation to Preparation, 3) Preparation to Action, and 4) Action to Maintenance. Our outcome measures and method of analysis must also be sensitive to these transitions between stages. Analysis of stage movement

would be able to detect intervention effects earlier by examining change among the earlier stages of change (e.g. Precontemplation and Contemplation). It would also allow analysis of the pattern of change and detection of differential treatment effects for different stages and the pattern of the differential effects over time. These types of analyses are essential for refining our research and treatment models.

If an intervention is mismatched to the person's stage of readiness to change, then the person is more likely to resist, drop out or be a treatment failure (DiClemente et al., 1991; Miller & Rollnick, 1991; Prochaska et al., 1992). Many treatment programs are designed to help people already ready for action and may be inappropriate for those who are not intrinsically motivated to change or who have much ambivalence. Stage matched interventions have shown promising results. Intervention programs for the majority of smokers in the Precontemplation, Contemplation, and Preparation stages have been developed (Prochaska et al., 1993) over the past 15 years. The most current technology available is used to apply behavioral principles based on the stages of change in a manner that models clinical interventions. An expert system has been used to individualize the interventions to the participant's stage and interact with them around the processes and principles that are necessary for them to progress (Prochaska et al., 2001a). The program is designed for an entire population of smokers not just those in the Preparation stage and has produced outcomes of 25% abstinence at 18-month follow-up (Prochaska et al., 1993).

Outcomes alone do not explain why a treatment does or does not work. Questions about treatment effectiveness cannot be completely answered, even with significant outcome results unless process evaluation can be used to support hypothesized mechanisms of action (DiClemente, Carrol, Connors & Kadden, 1994). We must be concerned with developing effective interventions and rigorous methodologies for testing them and demonstrating the conditions under which they are useful (Mattson & Donovan, 1994). Analysis of stage transitions over time combines outcome measures with process analysis. Recent advances in methodology improve our ability to incorporate stage as an outcome into a process analysis. A recent advancement is Latent Transition Analysis (LTA; Collins, Wugalter, & Rousculp 1991; Collins, Lanza, Schafer, & Flaherty, 2002), a method of analyzing categorical dynamic latent constructs over time.

Latent Transition Analysis

The current study uses LTA, an extension of latent class theory (Goodman, 1974), to estimate and test stage-sequential models of change. LTA is appropriate for discrete longitudinal data where change, development, or individual growth is of interest. LTA models may include both static and a dynamic part. The dynamic part of LTA models changes over time and can be considered the movement among the stages of change. The variable in LTA associated with the dynamic portion of the model is called latent status. The stages of change involve five latent statuses: Precontemplation (PC), Contemplation (C), Preparation (PR), Action (A), and Maintenance (M). Latent status is measured repeatedly over time and in the current

study it is measured four times: at baseline, and 6 months, 12 months, and 18 months after baseline. The static part of LTA models does not change over time and is used to divide the sample into groups. The variable in LTA associated with the static portion of the model is called latent class. Treatment group assignment is the static latent class in this study. The latent class division permits comparison of stage membership and stage transitions between two treatment groups.

LTA models involve five different types of parameters: 1) the gamma parameters (γ), which are estimates of the proportion of the population in each latent class, 2) the delta parameters (δ), which are estimates of the proportion of the population in each latent status at each occasion of measurement, conditional on latent class, 3) the tau parameters (τ) which are the conditional probabilities of transitioning from one latent status to another, 4) the rho parameters (ρ) for the dynamic latent status variable, which represent measurement error and are estimates of a particular item response conditional on latent status membership and 5) the rho parameters (ρ) for the static latent class variable, which represent measurement error, that are estimates of a particular item response conditional on latent class membership. The current study includes the first three types of parameters.

The gamma parameters represent the proportion in each latent class and in the current study are the proportion of the population in each of the two treatment groups. The delta parameters are the proportion of the population in each of the five latent statuses conditional on treatment group assignment. The delta

parameters reflect the proportion of the population in PC, C, PR, A, and M at each occasion for each treatment group. The tau parameter matrix is the transition probability matrix representing the probabilities of transitioning to each of the latent statuses, or stages, at each time, conditional on stage at the previous occasion and latent class (treatment group). There is one tau matrix for each latent class and is in our example a 5×5 matrix. When movement among stages can be either forward or backward, there is a full probability matrix. The diagonal elements of the tau matrix represent stability, i.e., the proportion of individuals who remain in the same latent status on both occasions of measurement. The elements above the diagonal represent progression. These values represent the proportion of individuals who move forward to a new latent status on the second occasion. The elements below the diagonal represent regression, i.e., the proportion of individuals who move backward to a previous latent status on the second occasion.

Until recently LTA used the Estimation Maximization (EM; Dempster, Laird, & Rubin, 1977) algorithm to produce maximum likelihood estimates for latent transition models. The maximum likelihood solution, however, does not provide standard errors. Recent advances in the LTA software (Collins, Schafer, Hyatt, & Flaherty, in preparation; Hyatt, Collins, & Schafer, 1999; Brunner, & Schafer, 1997) now use an Empirical Bayes approach, using data augmentation (DA; Schafer, 1997) for obtaining standard error estimates. Standard error estimates are useful in two ways: they provide a measure of uncertainty for each parameter estimate and they allow for hypothesis testing. Significance tests for

differences between parameter estimates are conducted on the DA estimates and standard errors.

Hypothesis testing of LTA parameters can be performed using differences of proportions or relative risk ratios. For differences in proportions, the null hypothesis of no difference is rejected if the confidence interval for the difference does not contain zero. The technical details of conducting hypothesis testing are found in Hyatt, Collins, & Schafer (1999).

Two previous studies have applied LTA to stages of change for smoking cessation in the adult population (Chapter 2, this volume; Martin, Velicer & Fava, 1996; Velicer, Martin & Collins, 1996). In the first study, LTA was used to test three alternative models of transitions among the stages of change for smoking cessation (Martin, Velicer & Fava, 1996). The models assessed movement among the stages for a two-year period. The model that fit the data best indicates that in a six-month period both progression and regression among the stages takes place as well as two-stage progression. Examination of the probability of movement among the stages revealed three findings consistent with the Transtheoretical Model. First, movement through the stages is not always linear. Second, the probability of forward movement is greater than backward movement. Third, the probability of moving to adjacent stages was greater than probability of two-stage progression.

The second study (Chapter 2, this volume) replicates previous descriptive findings and extended this program of research in two ways. First, LTA was applied inferentially to examine differential treatment effects for stage-matched

expert system intervention versus assessment control condition for smoking cessation in a sample of adult proactively recruited smokers. Second, analysis of stage transitions over time was examined as a process evaluation. The examination of the delta and tau parameter estimates demonstrated a strong intervention effect for the expert system intervention compared to the control. The effects of the intervention were strongest for the early stages and declined over time. However, there was less of the population in the early stages at the 18 and 24 month follow-ups. The study demonstrated utility of LTA as process analysis and the utility of LTA for detecting treatment effects descriptively. Several limitations were also demonstrated: evaluating alternate models and the potential for obscuring cumulative treatment effects due to lack of power and lack of sensitivity of data augmentation procedures.

The current study provides an empirical example of the application of LTA to the stages of change and smoking cessation among adults participating in a health maintenance organization. The application of latent transition methodology to the stages of change will be informative on two levels: methodological and theoretical. First, because the stage of change model is well researched and understood, it provides a platform to which the strengths and limitations of the latent transition methodology may be studied. Therefore, one can gauge the usefulness of LTA in contributing unique information to a well-studied phenomenon. Second, the applications to the stages of change will provide a more detailed picture of how people change over time as compared to what is found using traditional data

analytic techniques. The study will demonstrate the types of information obtained using LTA and the utility of LTA for examining group differences.

Method

The current study was conducted as a secondary analysis to data collected in a larger study (Velicer, Prochaska, Fava, Laforge, & Rossi, 1999). The purpose of the larger study was to compare an interactive expert system and non-interactive intervention for smoking cessation for an entire population of smokers and examine if a dose response relationship existed. A 2 Intervention (Interactive or Non-interactive) x 4 Contacts (1, 2, 3 or 6 contacts) x 4 Occasions (0, 6, 12, & 18 months) design was used.

In the larger study the primary outcomes was point prevalent abstinence at each follow-up. At each follow-up and for each of the four different series of contacts, the interactive expert system outperformed the non-interactive stage matched manuals. There was no clear dose response relationship for either the interactive or non-interactive interventions and there were no interaction effects so the design for the current study collapses to a 2 intervention X 4 occasions design.

Procedure

Screening was attempted through mail and telephone surveys of a total population of 24,178 adults in four offices of a managed care system in Rhode Island and southeastern Massachusetts and was completed on 19,236 participants. A total of 4,653 were identified as smokers, and 85% were recruited at baseline. Eligibility criteria included no serious illness, age between 18 and 75, and

competence in English. Of this group 2,882 were randomly assigned to one of the eight treatment groups. The remaining 1,085 participated in a separate intervention study designed to study enhancements to the expert-system intervention (Prochaska et al., 2001a). A full battery of smoking-related measures was mailed at baseline. Follow-up assessments by mail or phone occurred every 6 months. Intervention mailings occurred every 3 months.

Subjects were randomly assigned to an interactive Expert System intervention condition or a noninteractive intervention. Both interventions were delivered in one of four doses at three-month intervals. As dose was not an interest of this study the interactive and noninteractive interventions are compared collapsing across the levels of dosing.

Interventions

The interactive expert system is described in detail elsewhere (Velicer, Prochaska, Bellis, DiClemente, Rossi, Fava, & Steiger, 1993; Velicer, Rossi, Ruggier, & Prochaska, 1994). It involves a series of individualized computer reports. An assessment is completed on the key variables of the Transtheoretical Model, the scores are compared to a reference group and any previous scores for that individual, and a complex set of decision rules determine the most relevant intervention materials for that individual, which are then assembled into a feedback report. The 2 to 3 page, single-spaced reports are divided into four sections: (a) a description of the subject's current and previous stage of change, their pros and cons of quitting and feedback when necessary about their under-evaluating the pros

and over-evaluating the cons of quitting; (b) feedback on the subject's use of up to six change processes which describe how they compared normatively on each process with self-changers who were most successful in progressing to their next stage and how they compare ipsatively with their previous assessment; (c) a description of tempting situations with feedback on how to enhance self-efficacy in the most tempting situations; and, (d) a section on strategies for taking small steps to progress to the next stage, such as having those in the Contemplation stage delay the first cigarette of the day by an extra 30 minutes, a method of modeling smokers in the Preparation stage. The feedback reports also referred participants to sections of the stage-matched self-help that were most relevant to their individual progress.

The non-interactive self-help manuals were based on research on how self-changers progress through each stage of change and how they recycle through the stages if they relapse. (Velicer et al., 1994; Prochaska et al., 1992). The manuals instruct users about their particular stage of change and the processes they can use to progress to the next stage. Based on their pretest scores, treatment participants were sent the manual matched to their individual stage of change and the manuals for all subsequent stages. For smokers in the multiple contact conditions, a different manual was mailed on each occasion. Each smoker in each different stage at baseline received the same package of material; the only difference was the number of manuals received on each occasion.

Participants

The average age of the subjects ($N = 2,882$) in this study was 38.4

(SD=12.5). The sample was 56% female and 44% male and 37% had one year of college or more, 47% had graduated from high school, and 16% had less than a high school education. The baseline stage distribution of the sample was: Precontemplation, 37.2%; Contemplation, 44.7%; and Preparation, 18.1%. The stage distribution is approximately the same as reported in other representative samples (Velicer et al., 1995).

Method of Analysis

The analysis was performed using WinLTA (Collins, Lanza, Schafer, & Flaherty, 2002). First, LTA was used to specify a model that best explains movement between the stages over time and to examine transitions between the stages. A good fitting model will have predictions that are close to the actual data. The goodness of fit statistic will be small relative to degrees of freedom for a good fitting model (Graham, Collins, Wuglater, Chung, & Hansen, 1991). G^2 , a likelihood-ratio goodness-of-fit statistic, is approximately distributed as a chi-square where degrees of freedom is equal to the number of response patterns minus the number of estimated parameters minus one.

A model building approach was used in model testing where each subsequent model added transition probability parameters to the previous model. Five nested models, similar to models in previous studies (Martin et al., 1996; Evers, Harlow, Redding, & LaForge, 1998), were compared for goodness of fit using double crossvalidation (Cudeck & Browne, 1983). Double crossvalidation involves identifying a set of plausible models, estimating parameters separately in

each half of a randomly split sample, and the computing two fit indices by applying each model as fitted in one half to the opposite half of the sample. The crossvalidation fit indices are examined and the model with the best indices is selected. Figure 3 presents the five models. Model 1 proposes one stage forward movement. Model 2 proposes one stage forward and backward movement. Model 3 proposes one stage forward and backward movement and two stage forward movement. Model 4 proposes one stage forward and backward movement, two-stage forward movement, and two stage backward movement. Model 5 proposes one stage forward and backward movement, two stage forward and backward movement, and three stage forward movement. Nested models are compared by subtracting the values of G^2 and associated degrees of freedom.

Second, delta parameter and tau parameter estimates are analyzed descriptively. The delta parameters provide information of how the stage membership (proportion of the population in each stage) changes over time. The tau parameters provide detailed information on the probability of transitioning from one stage to another conditional on treatment group and previous stage. Third, differential treatment effects are examined using data augmentation procedures to test a series of planned comparison comparing delta and tau parameter estimates between treatment and control conditions. Fourth, an application of how LTA data can be examined as a process evaluation is provided. The LTA routine for incomplete data was used so all cases could be employed at all time points. The procedure is based on computational techniques developed to handle missing data

Figure 3

Five alternate nested models

Model 1

Model 2

Model 3

Model 4

Model 5

in contingency tables (Schafer, 1997) and is robust when the data are missing completely at random or missing at random (Hyatt & Collins, 1998).

Results

Overall Model Fit

Following the recommendation of Cudeck & Brown (1983) double crossvalidation procedures were used to specify models and compare model fit. The sample was randomly split into two samples, A and B, and parameter values for each of the five models were estimated separately in each half and then fit indices were computed by applying each model as fitted in one half to the opposite half of the sample.

Table 7 displays the G^2 and degrees of freedom results of the double crossvalidation procedure for the five models. The results are presented for half the sample, labeled Sample A, and then for the other half of the sample, labeled Sample B. Results of the initial model estimation on each half of the sample are in the columns labeled Calibration G^2 . Results of each model as fitted in one half of the sample as applied to the opposite half are presented in the columns labeled Crossvalidation G^2 . Overall model fit for the five models is carried out by comparing model fit statistics using G^2 difference tests. G^2 difference tests are presented in Table 8. A nonsignificant value of G^2 difference suggests the overall fits of the two models are comparable. A significant result supports retaining the parameters added by the larger model. Assuming the G^2 difference is distributed as

Table 7

Results of Crossvalidation on Sample Split Randomly into Samples A and B

		Sample A		Sample B	
		Calibration G^2 on A	Cross- Validation G^2 on B	Calibration G^2 on B	Cross- Validation G^2 on A
Model 1	G^2 df	2072.96 1217	2098.24	2057.05 1217	2114.83
Model 2	G^2 df	1530.73 1199	1607.09	1534 1199	1605.26
Model 3	G^2 df	1181.97 1181	1278.59	1162.47 1181	1291.29
Model 4	G^2 df	1138.45 1169	1240.25	1096.68 1169	1258.84
Model 5	G^2 df	909.86 1161	1064.77	906.39 1169	1051.80

Note. Model 1 proposes one stage forward movement. Model 2 proposes one stage forward and backward movement. Model 3 proposes one stage forward and backward movement and two stage forward movement. Model 4 proposes one stage forward and backward movement, two-stage forward movement, and two stage backward movement. Model 5 proposes one stage forward and backward movement, two stage forward and backward movement, and three stage forward movement.

Table 8

Results of G^2 Difference Tests Comparing Nested Models on Sample Split Randomly into Samples A and B

	Sample A		Sample B	
	G^2 difference	df	G^2 difference	df
Model 1-2	491.15	18*	509.57	18*
Model 2-3	328.51	18*	313.97	18*
Model 3-4	38.34	12*	32.45	12*
Model 4-5	175.48	8*	207.04	8*

* $p < .001$

chi-square, the more restrictive models represents a significant decrement in model fit compared with the more general model.

A significant G^2 difference was found between Model 4 and Model 5, which typically suggests retaining the larger model (in this case Model 5). However, Model 4 was selected over Model 5 as the best fitting model despite the significant G^2 difference test between the two models for several reasons. First, examination of the residuals indicated that the transitions added to Model 5 (PC to A and C to M) were represented in a very small proportion of the sample (.018% from baseline to 6 months, .009% from 6 to 12 months, and .007% from 12 to 18 months). Second, the purpose of model specification is to parsimoniously explain the observations, using the least number of parameters as possible. Any given model predicts the number of people who contribute to a particular response pattern. A good fitting model will have predictions that are close to the actual data. The additional transitions of Model 5 account for a small proportion of the observed data and therefore are not theoretically meaningful despite being statistically significant. Third, the limitations of the G^2 fit index warrant a closer examination of the results. When the absolute magnitude of the change in large parameter estimate is small as is true in this case, then significance may be due more to the sample size than to the size of the effect (Kline, 1998). And as noted earlier LTA models tend to involve large contingency tables. Under these conditions the G^2 is usually not distributed as a chi-square so overall hypothesis testing can be done in only an approximate way (Collins, Fidler, Wugalter, & Long, 1993).

Invariance of the models was tested by running each of the models on each treatment group independently. Model fit was approximately the same within each group.

Gamma Parameter Estimates (Probabilities of Latent Class Membership)

The gamma parameters represent the proportion of the population in each of the two latent classes or in this case treatment groups. Fifty percent (95%CI) of the population was in the intervention group and 50% (95%CI) was in the control group.

Delta Parameter Estimates (Probabilities of Latent Status Membership)

The delta parameters are the proportion of the population in each of the latent statuses (e.g. stages) at each time conditional on latent class (e.g. treatment assignment). The delta parameter estimates and confidence intervals are presented in Table 9. It was hypothesized that at follow-up the intervention group would have lower probabilities of being in the Precontemplation and Contemplation stages of change and have higher probabilities of being in the Preparation, Action, and Maintenance stages of change compared to the control group. There was mixed support for this hypothesis. At each follow-up the intervention group has a lower proportion in Precontemplation (.352 at 6 months, .379 at 12 months, .376 at 18 months) compared to the control group (.369 at 6 months, .404 at 12 months, .411 at 18 months). The intervention group has a lower proportion in Contemplation at 12 months and 18 months (.317 at 12 months, .298 at 18 months)

Table 9

Estimates and 95% CI of Delta (δ) Parameters, Probabilities of Latent Status Membership

	Baseline	6 Months	12 Months	18 Months
<u>Precontemplation</u>				
Intervention	.374 [.372-.377]	.352 [.344-.356]	.379 [.372-.386]	.376 [.366-.386]
Control	.356 [.352-.355]	.369 [.364-.374]	.404 [.400-.409]	.411 [.404-.417]
<u>Contemplation</u>				
Intervention	.456 [.454-.458]	.377 [.372-.383]	.317 [.309-.324]	.298 [.289-.306]
Control	.462 [.460-.464]	.372 [.365-.379]	.337 [.333-.341]	.311 [.304-.318]
<u>Preparation</u>				
Intervention	.168 [.167-.170]	.167 [.164-.170]	.149 [.145-.152]	.134 [.126-.141]
Control	.182 [.180-.184]	.178 [.171-.179]	.149 [.144-.153]	.130 [.127-.133]
<u>Action</u>				
Intervention	.0	.104 [.100-.108]	.098 [.095-.101]	.089 [.084-.093]
Control	.0	.082 [.078-.086]	.071 [.067-.075]	.080 [.078-.083]
<u>Maintenance</u>				
Intervention	.0	.0	.057 [.542-.059]	.103 [.099-.107]
Control	.0	.0	.037 [.035-.039]	.067 [.064-.070]

Note. A value of .0 indicates that the parameter was fixed at zero.

compared to the control group (.337 at 12 months, .311 at 18 months) but at 6 months the proportion in Contemplation is similar for the intervention group (.377) and control group (.372).

At 6 months the intervention group has a lower proportion in Preparation (.167) compared to the control group (.178). At 12 months and 18 months the proportion in Preparation is similar for the intervention group (.149 at 12 months, .134 at 18 months) and the control group (.149 at 12 months, .130 at 18 months).

At each follow-up the intervention group has a higher proportion in Action (.104 at 6 months, .098 at 12 months, .089 at 18 months) compared to the control group (.082 at 6 months, .071 at 12 months, .080 at 18 months). At each follow-up the intervention group has a higher proportion in Maintenance (.057 at 12 months, .103 at 18 months) compared to the control group (.037 at 12 months, .067 at 18 months).

It was also hypothesized that the proportion in Precontemplation, Contemplation, and Preparation would decrease over time and that the membership in Action and Maintenance would increase over time. The results for the Precontemplation, Contemplation, Preparation, and Maintenance stages support this hypothesis. The pattern of delta parameter values over time differs for Precontemplation across the intervention and control groups. In the intervention group, Precontemplation membership decreases from baseline (.374) to 6 months (.352), increases at 12 months (.379), and remains stable at 24 months (.376). In the control group the proportion in Precontemplation increases (.356 at baseline,

.369 at 6 months, .404 at 12 months, .411 at 18 months). Contemplation membership decreases for both groups. In the intervention group the proportion in Contemplation decreases (.456 at baseline, .377 at 6 months, .317 at 12 months, .298 at 18 months). In the control group the proportion in Contemplation decreases (.462 at baseline, .372 at 6 months, .337 at 12 months, .311 at 18 months).

Preparation membership decreases for both groups. In the intervention group the proportion in Preparation decreases (.168 at baseline, .167 at 6 months, .149 at 12 months, .134 at 18 months). In the control group the proportion in Preparation decreases (.182 at baseline, .178 at 6 months, .149 at 12 months, .130 at 18 months). The pattern of delta parameters for Action differs across the treatment groups. The proportion in Action declines over time for the intervention group (.104 at 6 months, .098 at 12 months, .089 at 18 months). For the control group, the proportion in Action decreases at 12 months (.082 at 6 months, .071 at 12 months) and then increases at 18 months (.080). Membership in Maintenance increases for both groups. The intervention group membership increases from .057 at 12 months to .103 at 18 months. In a similar fashion, the control group membership increases from .037 at 12 months to .067 at 18 months.

Tau Parameter Estimates (Probabilities of Latent Status Transitions)

A specific interest of this study is the difference between the intervention group and control group in overall transitions among the stages of change. The tau parameters represent the conditional probability of transitioning to a particular stage of change given the previous stage of change and the treatment group

assignment. The tau parameter estimates and the associated 95% confidence intervals are presented in matrix form in Table 10. Figure 4 displays the tau parameter estimates graphically. Examination of the tau parameter matrices in Table 10 provides very detailed information regarding the probability of transitioning from one stage of change to another (conditional on previous stage of change and treatment group). The cells above the diagonal indicate advancement in stage, or progression. The cells along the diagonal indicate no change in stage, or stability. The cells below the diagonal indicate returning to a previous stage, or regression.

Several general observations can be made about the pattern of the transition probabilities. First, the probability of transition to adjacent stages was greater than to nonadjacent stages. Although two-stage progression or regression within a six-month period is possible, it is more probable to transition to the next stage. The probability of progression from Precontemplation to Preparation is .009 at its lowest (for the control group at 6 months) and .057 at its highest (for the intervention group at baseline). The probability of progression from Contemplation to Action is .062 at its lowest (for the control group at 6 months) and .129 at its highest (for the intervention group at baseline). The probability of progression from Preparation to Maintenance is less than .01 at all time points for both groups. The probability of regression from Action to Contemplation is .030 at its lowest (for the intervention group at 12 months) and .160 at its highest (for the control

Table 10

Estimates and 95 % CI of Tau (τ) Parameters, Probabilities of Latent Status Transitions

Baseline Stage of Change	6 Month Stage of Change				
	PC	C	PR	A	M
Intervention Group					
Precontem- plation	.736 [.679-.787]	.207 [.155-.268]	.057 [.032-.098]	.0	.0
Contem- plation	.154 [.120-.195]	.558 [.511-.603]	.159 [.128-.196]	.129 [.101-.163]	.0
Preparation	.026 [.006-.093]	.269 [.205-.344]	.433 [.351-.519]	.267 [.194-.354]	.004 [.000-.055]
Action	.0	.0	.0	1.000	.0
Mainte- nance	.0	.0	.0	.0	1.000
Control Group					
Precontem- plation	.795 [.749-.835]	.161 [.124-.205]	.044 [.023-.080]	.0	.0
Contem- plation	.170 [.134-.213]	.576 [.524-.626]	.147 [.114-.186]	.107 [.075-.149]	.0
Preparation	.050 [.023-.102]	.268 [.211-.333]	.503 [.432-.574]	.177 [.129-.237]	.002 [.000-.032]
Action	.0	.0	.0	.0	.0
Mainte- nance	.0	.0	.0	.0	1.000

Table 10 (continued)

6 Month Stage of Change	12 Month Stage of Change				
	PC	C	PR	A	M
<u>Intervention Group</u>					
Precontem- plation	.856 [.803-.898]	.119 [.080-.172]	.025 [.012-.048]	.0	.0
Contem- plation	.198 [.148-.258]	.554 [.497-.607]	.140 [.104-.184]	.109 [.080-.145]	.0
Preparation	.027 [.003-.141]	.367 [.287-.453]	.400 [.324-.481]	.202 [.144-.274]	.004 [.000-.049]
Action	.0	.043 [.001-.424]	.197 [.108-.325]	.225 [.125-.363]	.535 [.427-.641]
Mainte- nance	.0	.0	.0	.0	1.000
<u>Control Group</u>					
Precontem- plation	.845 [.796-.885]	.146 [.103-.201]	.009 [.001-.043]	.0	.0
Contem- plation	.232 [.190-.279]	.565 [.507-.622]	.141 [.107-.183]	.062 [.036-.103]	.0
Preparation	.036 [.013-.089]	.367 [.293-.447]	.444 [.372-.578]	.151 [.100-.220]	.002 [.000-.030]
Action	.0	.102 [.004-.611]	.186 [.105-.303]	.267 [.160-.404]	.445 [.324-.573]
Mainte- nance	.0	.0	.0	.0	1.000

Table 10 (continued)

12 Month Stage of Change	18 Month Stage of Change				
	PC	C	PR	A	M
<u>Intervention Group</u>					
Precontem- plation	.806 [.724-.870]	.178 [.121-.251]	.016 [.001-.144]	.0	.0
Contem- plation	.204 [.161-.255]	.560 [.494-.624]	.141 [.096-.199]	.096 [.056-.155]	.0
Preparation	.037 [.001-.392]	.336 [.244-.441]	.503 [.408-.598]	.120 [.062-.214]	.004 [.000-.051]
Action	.0	.030 [.001-.329]	.081 [.018-.255]	.340 [.201-.508]	.549 [.402-.689]
Mainte- nance	.0	.0	.015 [.001-.156]	.131 [.037-.335]	.855 [.650-.954]
<u>Control Group</u>					
Precontem- plation	.836 [.780-.882]	.151 [.108-.206]	.012 [.003-.041]	.0	.0
Contem- plation	.182 [.141-.230]	.548 [.482-.613]	.164 [.127-.209]	.107 [.075-.149]	.0
Preparation	.074 [.040-.133]	.356 [.269-.452]	.421 [.333-.515]	.145 [.092-.219]	.003 [.000-.040]
Action	.0	.160 [.053-.363]	.104 [.026-.298]	.298 [.189-.434]	.438 [.323-.559]
Mainte- nance	.0	.0	.013 [.001-.161]	.051 [.003-.339]	.937 [.708-.992]

Note. A value of .0 indicates that the parameter was fixed at zero.

Figure 4

Tau parameter estimates. Intervention group estimates are marked in italics type and control group estimates are in parentheses.

Baseline to 6 Months

6 Months to 12 Months

12 Months to 18 Months

group at 12 months). The probability of regression from Maintenance to Preparation is .015 for the intervention group and .013 for the control group.

Second, for three stages, Precontemplation, Contemplation, and Maintenance, the probability of remaining at the same stage from one time point to the next was greater than the probability of transitioning to all other stages combined. The probability of remaining in Precontemplation for the intervention group was .736 at baseline, .856 at 6 months, and .806 at 12 months. The probability of remaining in Precontemplation for the control group was .795 at baseline, .845 at 6 months, and .836 at 12 months. The probability of remaining in Contemplation for the intervention group was .558 at baseline, .554 at 6 months, and .560 at 12 months. The probability of remaining in Contemplation for the control group was .576 at baseline, .565 at 6 months, and .548 at 12 months. The probability of remaining in Maintenance was .855 for the intervention group and .937 for the control group at 12 months.

Third, the probability of transitioning is the highest for Action. The probability of remaining in Action for the intervention group was .225 at 6 months and .340 at 12 months. The probability of remaining in Action for the control group was .267 at 6 months and .298 at 12 months. These estimates indicate a high degree of instability in the Action stage.

It was hypothesized that the probability of progression would be greater than regression for any stage across both the intervention and control groups. The probability of progression is calculated by summing transition probabilities above

the diagonal element for each stage. The probability of regression is calculated by summing the transition probabilities below the diagonal element for each stage. This hypothesis was supported in both the intervention group and the control group except for the Preparation stage that consistently had greater regression than progression. For the intervention group, the probability of progression was greater than regression for Contemplation from baseline to 6 months (.288 vs. .154) and 12 months to 18 months (.237 vs. .204), but not from 6 months to 12 months (.249 vs. .198). For the control group, the probability of progression was greater than regression for Contemplation from baseline to 6 months (.254 vs. .170), and 12 months to 18 months (.271 vs. .182), but not from 6 months to 12 months (.203 vs. .232). For the intervention group, the probability of progression was greater than regression for Action from 6 months to 12 months (.535 vs. .240), and 12 months to 18 months (.549 vs. .111). For the control group, the probability of progression was greater than regression for Action from 6 months to 12 months (.445 vs. .288), and 12 months to 18 months (.438 vs. .264). For the intervention group, the probability of regression was greater than progression for Preparation from baseline to 6 months (.271 vs. .295), 6 months to 12 months (.206 vs. .394), and 12 months to 18 months (.124 vs. .373). For the control group, the probability of regression was greater than progression for Preparation from baseline to 6 months (.179 vs. .318), 6 months to 12 months (.153 vs. .403), and 12 months to 18 months (.148 vs. .430).

It was hypothesized that intervention group would experience less regression and more progression among the stages compared to the control group. There was mixed support for this hypothesis. For Precontemplation, the probability of progressing is higher for the intervention group (.264 from baseline to 6 months, .194 from 12 to 18 months) than the control group (.205 from baseline to 6 months, .163 from 12 to 18 months) except from 6 to 12 months where the probability of progressing is lower in the intervention group (.144) than the control group (.155). For Contemplation, the probability of progressing is higher for the intervention group only from baseline to 6 months (.288 from baseline to 6 months, .249 from 6 to 12 months, .237 from 12 to 18 months) compared to the control group (.254 from baseline to 6 months, .203 from 6 to 12 months, .271 from 12 to 18 months). The probability of regressing is lower in the intervention group (.154 from baseline to 6 months, .198 from 6 to 12 months, .204 from 12 to 18 months) compared to the control group (.170 from baseline to 6 months, .232 from 6 to 12 months, .182 from 12 to 18 months) except from 18 to 24 months.

For Preparation, the probability of progressing is higher for the intervention group (.271 from baseline to 6 months, .206 from 6 to 12 months) than the control group (.179 from baseline to 6 months, .153 from 6 to 12 months) except from 12 to 18 months where the probability of progressing is lower in the intervention group (.124) than the control group (.148). At all times the probability of regressing is lower in the intervention group (.295 from baseline to 6 months, .394

from 6 to 12 months, .373 from 12 to 18 months) than the control group (.318 from baseline to 6 months, .403 from 6 to 12 months, .430 from 12 to 18 months).

For Action, the probability of progressing is higher for the intervention group (.535 from 6 to 12 months, .549 from 12 to 18 months) than the control group (.445 from 6 to 12 months, .438 from 12 to 18 months) and the probability of regressing is lower in the intervention group (.240 from 6 to 12 months, .111 from 12 to 18 months) than the control group (.288 from 6 to 12 months, .264 from 12 to 18 months). For Maintenance, the probability of regressing is higher for the intervention group (.146 from 12 to 18 months) than the control group (.064 from 12 to 18 months)

Overall, there is a pattern in the tau parameter values that indicate the intervention group has some better outcomes compared with the control group.

Results of Tests of Hypotheses

Tests of significance were conducted to examine hypotheses about group differences in delta parameters and the tau parameters. Results from these tests based on the differences of proportions are presented. For differences of proportion, the null hypothesis of no difference is rejected if the confidence interval for the difference does not contain zero.

Several tests of delta parameters reach statistical significance as shown in Table 11. At 12 months, those in the intervention group are significantly more likely to be in Action ($\delta=.098$) compared with the control group ($\delta=.071$). Also, at 12 months, those in the intervention group are significantly more likely to be in

Table 11

Hypothesis Testing: Differences of Proportions and 95% CI for Delta (δ) Parameters

	Baseline	6 months	12 months	18 months
Precontemplation	.020 [-.015-.056]	.019 [-.021-.059]	.025 [-.020-.071]	.035 [-.017-.087]
Contemplation	.006 [-.031-.043]	.005 [-.035-.046]	.021 [-.022-.063]	.013 [-.027-.054]
Preparation	.014 [-.014-.042]	.009 [-.019-.037]	.001 [-.031-.031]	.003 [-.026-.033]
Action	.0	.022 [-.003-.047]	.027* [.005-.048]	.008 [-.017-.034]
Maintenance	.0	.0	.020 [.002-.038]	.037* [.011-.062]

* $p < .05$

Table 12

Hypothesis Testing: Differences of Proportions and 95% CI for Tau (τ) Parameters

Baseline Stage of Change	6 Month Stage of Change				
	PC	C	PR	A	M
Precontem- plation	.059 [-.007-.125]	.046 [-.015-.108]	.013 [-.021-.047]	---	---
Contem- plation	.016 [-.029-.061]	.018 [-.046-.082]	.012 [-.030-.055]	.023 [-.027-.070]	---
Preparation	.024 [-.020-.068]	.001 [-.051-.053]	.071 [-.033-.174]	.091 [-.008-.190]	.002 [-.011-.014]
6 Month Stage of Change	12 Month Stage of Change				
	PC	C	PR	A	M
Precontem- plation	.011 [-.038-.061]	.027 [-.027-.082]	.016 [-.006-.038]	--	--
Contem- plation	.034 [-.021-.089]	.011 [-.058-.080]	.001 [-.047-.049]	.047* [.001-.091]	--
Preparation	.009 [-.028-.046]	.000 [-.109-.109]	.044 [-.056-.143]	.051 [-.034-.135]	.002 [-.006-.010]
Action	--	.059 [-.060-.179]	.012 [-.111-.134]	.042 [-.114-.198]	.090 [-.059-.239]

Table 12 (continued)

12 Month Stage of Change	18 Month Stage of Change				
	PC	C	PR	A	M
Precontem- plation	.030 [-.050-.110]	.027 [-.045-.099]	.003 [-.019-.026]	--	--
Contem- plation	.022 [-.034-.079]	.012 [-.073-.096]	.023 [-.038-.084]	.011 [-.045-.067]	--
Preparation	.038 [-.026-.102]	.020 [-.096-.136]	.083 [-.037-.203]	.025 [-.056-.107]	.001 [-.008-.010]
Action	--	.131 [-.001-.262]	.023 [-.093-.139]	.042 [-.143-.226]	.112 [-.070-.295]
Mainte- nance	--	--	.005 [-.034-.045]	.084 [-.043-.211]	.089 [-.036-.215]

*p < .05

Maintenance ($\delta=.057$) compared with the control group ($\delta=.037$). At 24 months, those in the intervention group are significantly more likely to be in Maintenance ($\delta=.103$) compared with the control group ($\delta=.067$). The differences at baseline and 6 months were not significant. One of the tau parameters reached significance. Table 12 presents the differences of proportions and 95% CI for the tau parameters. From 6 to 12 months, the probability of progressing from Contemplation to Action is higher for the intervention group ($\tau=.109$) than for the control group ($\tau=.062$).

Process Evaluation

The purpose of the process evaluation is to identify when and what stages of change the intervention is most effective by examining the delta and tau parameters over time. The delta parameters represent the growth and decline of stage membership over time. What is shown in the pattern of delta parameters is that the intervention group reduces membership in the early stages of Contemplation and Preparation and increases membership in Maintenance. The intervention group has lower proportions in the early stages of Precontemplation and Contemplation compared with the control group and higher proportions in the late stages. For Contemplation, membership is lower for the intervention group and declines over time. Membership in Maintenance is higher for the intervention group and grows over time. The intervention group has less of the population in Precontemplation compared to the control group, but the proportion in Precontemplation increases at 12 months and then remains stable at 18 months. Preparation stage has about the same outcomes for both groups.

Examination of the pattern of tau parameter values over time also provides valuable information about when and for which stages of change the intervention is most effective. The tau parameters are evaluated *between groups* and *over time*. A favorable *between groups* outcome for the intervention group is marked by higher probabilities of progressing one or two stages compared to the control group. It is likely that if there is higher probability of progressing within the stages the probability of regressing back one or two stages is lower. From baseline to 6 months the intervention group outperforms the control group for all stages. From 6 months to 12 months the intervention group continues to outperform the control group with the exception of the Precontemplation stage where there is a greater probability of remaining in Precontemplation and less progression from Precontemplation to Contemplation. From 12 months to 18 months the intervention group outperforms the control group for Precontemplation and Action. The intervention group has poorer outcomes compared to the control group for Contemplation and Maintenance and mixed outcomes for Preparation.

A favorable outcome for the intervention group *over time* is marked by the transition probabilities decreasing for the regression parameters and increasing for the progression parameters. The favorable outcomes for Precontemplation are strongest from baseline to 6 months and 12 to 18 months. The favorable outcomes for Contemplation decline by 6 to 12 months. By 6 to 12 months the probability of remaining in Contemplation increases and the probability of progressing decreases. Similar to Precontemplation, the favorable outcomes for Preparation are strongest

from baseline to 6 months and 12 to 18 months. The Action stage outcomes are better for the 12 to 18 month transitions with increased progression and less regression.

The delta parameter and tau parameter information taken together provide another level of information than either of the parameters alone. The results from the delta parameters show the best outcomes for Contemplation and Maintenance, and mixed outcomes for Precontemplation and Action. The tau parameters show that the intervention effects are strongest for Precontemplation and Preparation from baseline to 6 months and 12 to 18 months and strongest for Contemplation, Preparation, and Maintenance from baseline to 12 months. Precontemplation and Preparation appear to need additional intervention to maintain the favorable outcomes consistently.

Discussion

The results of this study provide information about latent transition methodology and the application of this methodology to the stages of change for smoking cessation. The study examined model specification, the pattern of parameter values, statistical tests for treatment group differences, and the utility of LTA for a process analysis. The type of information obtained using LTA and the utility of LTA for examining group differences was demonstrated.

Examination of the parameter estimates generated using LTA demonstrates a pattern of results indicating treatment effects for the expert system intervention consistent with the findings in the proactively recruited population of smokers

presented in Chapter 2. The delta estimates, representing the proportion of the population in each stage at each time point conditional on treatment group, differed between the intervention group and control group. The delta parameters show that the intervention group has lower proportions in Precontemplation and Contemplation and higher proportions in Action and Maintenance compared to the control group. This suggests that the expert system intervention is effective at helping people to make a cessation attempt and in some instances maintain the quit. A greater number of subjects were engaged in attempts to quit smoking in the intervention group; hence the greater increase in Action stage membership.

The pattern of the delta parameter values over time also differed between the two treatment groups consistent with the findings presented in Chapter 2. The two groups had noticeable membership differences in Precontemplation and Action. Precontemplation membership mostly decreases for the intervention group but increases for the control group indicating better outcomes for the expert system. However, Action membership decreases for the intervention group and both decreases and increases for the control group. These results suggest that the intervention is particularly effective for people who were not previously thinking about changing their smoking. Historically, this group of people has been the most challenging group to transition to making changes.

The tau parameter pattern indicates an intervention effect. There is less regression to an earlier stage and more progression to a later stage in the intervention group. The magnitude of the effect decreases over time suggesting

that the intervention is beneficial closer to when it was administered. In the case of this study the intervention effect of the expert system die out over time especially for the early stages. These results replicate those found in Chapter 2.

Although movement between the stages is very dynamic, results presented here indicate that smokers and former smokers are more likely to transition to the nearest stage as found in previous studies (Chapter 2, this volume; Martin, Velicer, & Fava, 1996). Two-stage progression or regression is less probable than moving to adjacent stages. This observation has implication for intervention design. It had previously been suggested that targeting stage-matched interventions at helping smokers progress one stage would be beneficial to smokers.

A model building approach was used in model testing where each subsequent model added transition probability parameters to the previous model. Similar to results of Chapter 2, the G^2 difference test comparing the five nested models failed to retain the null hypothesis of no differences between any two models. The model that specified two-stage forward and backward movement, Model 4, was selected as the best fitting model. From a purely statistical approach, Model 5 provided the best fit to the data. The absolute magnitude of the change in the two parameters added to Model 5 when freely estimated was very low and therefore the significance may be due more to the sample size than to the size of the effect (Kline, 1998; Hu & Bentler, 1995). The growing dissatisfaction with the chi-square goodness-of-fit test has led to the generation of a growing number of adjunct fit indexes within SEM (Hoyle, 1995). It is likely that a similar trend will develop

within latent transition methodology. Despite the weakness of the goodness-of-fit test the information provided by latent transition methodology is quite valuable.

The transition probability estimates provide a detailed look at movement among the stages of change conditional on previous stage and treatment group. Data augmentation procedures applied to the tau parameters allowed for testing of group differences. This allows for a very in depth examination of movement among the stages. This level of specificity, however, obscures the cumulative effect that there may be in two ways. First, typical point prevalence combines the Precontemplation, Contemplation, and Preparation stages and compares this proportion to the proportion in Action and Maintenance combined. The difference tested with a point prevalence estimate will be larger than the conditional proportions being compared within LTA. Second, point prevalence examines outcome at only one follow-up period. LTA results provided a detailed picture at each of several follow-up periods. Therefore, the cumulative effect seen with point prevalence is divided up among the three follow-up periods. The original study was powered to detect treatment effects in a certain range of potential outcomes, specifically for the proportion of subjects moving into the Action and Maintenance stages. The proportions of the transition probabilities differ from those for which the study was powered to detect, therefore, the test for treatment differences within LTA may lack sufficient power.

This study has served two broad purposes. First, it has demonstrated the utility of latent transition methodology for the study of change. Several strengths

of the method have been demonstrated: estimation of latent status membership, estimation of latent transition probabilities, and the utility of employing LTA as a process analysis. Several limitations of the method have been demonstrated: testing alternate models, the potential obscuring of cumulative treatment effects found with traditional methods, and the lack of sensitivity of data augmentation procedures for testing group differences. Second, this study has demonstrated the utility of employing stage of change as an outcome measure. Stage membership is sensitive to change for all smokers, not just those achieving Action criteria.

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Chapter 4

Evaluating an Expert System Intervention for Smoking Cessation in a Population of Parents

Changing behaviors to result in better health is the focus of many health promotion programs. These programs are designed to have the highest impact on the target population. Impact is defined as the efficacy rate (percent of population reaching the criterion behavior change) times the participation rate (the percent of the target population reached by the program) (Velicer & Prochaska, 1999). Most smoking cessation intervention programs suffer from limited impact for several reasons. First, the programs are action-oriented, designed for those ready to quit, and therefore are inappropriate up to 80% of smokers (Velicer, Fava, Prochaska, Abrams, Emmons & Pierce, 1995). Second, the programs rely on reactive recruitment that results in low participation rates, typically 1-5% (Schmid, Jeffrey, & Hellerstedt, 1989). The combination of action-oriented interventions and reactive recruitment cannot have much impact on the number one public health problem, smoking.

Two ways to increase impact are to increase either efficacy of interventions or participation rates. Highest participation rates, 80 to 85%, are obtained with proactive recruitment (Prochaska, Velicer, Fava, Rossi, & Tsoh, 2001a; Prochaska, Velicer, Fava, Ruggiero, LaForge, Rossi, Johnson, & Lee, 2001b; Velicer, Prochaska, Fava, LaForge, & Rossi, 1999). Proactive recruitment approaches contact the target population directly and offer the services to them. With such a

high proportion of the population participating, delivery of the intervention to a high proportion of the target population is permitted. Participation rates this high include the majority of smokers who would not be recruited using reactive recruitment. This includes approximately 40% in the Precontemplation stage (not planning to quit in the next 6 months) and 40% in the Contemplation stage (planning to quit in the next 6 months) as well as the 20% in the Preparation stage (ready to quit in the next 30 days). If an intervention is mismatched to a person's stage of readiness to change, then the person is more likely to resist, drop out or be a treatment failure (DiClemente, Prochaska, Fairhurst, Velicer, Velasquez, & Rossi, 1991; Miller & Rollnick, 1991; Prochaska, DiClemente, & Norcross, 1992). Population based interventions must be effective with the majority who are not considering quitting.

In the area of smoking cessation stage-matched interventions have been used to produce unprecedented impacts in population-based trials (Prochaska et al., 2001a). Intervention programs for the majority of smokers not planning to quit have been developed over the past 15 years (Prochaska, DiClemente, Velicer, & Rossi, 1993). Programs are now available that apply behavioral principals based on the stages of change in a manner that models clinical interventions using the most current technology. The expert system is individualized to the person's stage of change and interacts with them around the processes and principles that are necessary for them to progress (Prochaska et al., 2001a). These interactive stage-based technologies have consistently generated 23 to 25% point prevalence at 18 to

24 month follow-ups (Prochaska et al., 1993; 2001a; 2001b; Velicer et al., 1999, Prochaska & Velicer, 1999). Increasing the efficacy of the expert system, however, has been unsuccessful (Prochaska et al., in preparation).

An alternative to increasing efficacy and participation is to intervene on multiple behaviors rather than one behavioral risk as a means of enhancing the total population impact for health promotion and disease prevention (Prochaska et al., in preparation). The impacts of simultaneous stage-matched expert systems for multiple behaviors have not yet been demonstrated and there is no consistent support for the efficacy of changing multiple health behaviors on a population basis. The research, however, is limited by quasi-experimental designs, action-oriented interventions with low participation rates, and lack of the most promising interventions (Prochaska, Wing, Orleans, White, Broomfield & Wilson, 2001). A study was designed to overcome these limitations that targeted three of the most important behavioral risks for the prevention of cancer and other chronic diseases: smoking, diet, and sun exposure (Prochaska et al., in preparation). The interventions were based on state of the art stage-based expert systems and were appropriate for all members of the target population. At 24 month follow-up the expert system out performed the comparison condition across risk behaviors, resulting in 22% of participants in Action or Maintenance for smoking, 33.5% for diet and 29.7% for sun exposure.

The current study is secondary data analysis of this larger study. The purpose of this study is to examine in a more detailed fashion the smoking

outcomes at 12 and 24 months. Outcomes alone do not explain why a treatment does or does not work. Questions about treatment effectiveness cannot be completely answered, even with significant outcome results, unless process evaluation can be used to support hypothesized mechanisms of action (DiClemente, Carrol, Connors & Kadden, 1994). Analysis of stage transitions over time combines outcome measures with process analysis. Recent advances in methodology improve our ability to incorporate stage as an outcome into a process analysis. One such advancement is Latent Transition Analysis (LTA; Collins, Wuglater, & Rousculp, 1991; Collins & Wuglater, 1992), a method of analyzing categorical dynamic latent constructs over time.

Latent Transition Analysis

The current study uses LTA, an extension of latent class theory (Goodman, 1974), to estimate and test stage-sequential models of change. LTA is appropriate for discrete longitudinal data where change, development, or individual growth is of interest. LTA models may include both static and a dynamic part. The dynamic part of LTA models changes over time and can be considered the movement among the stages of change. The variable in LTA associated with the dynamic portion of the model is called latent status. The stages of change involve five latent statuses: Precontemplation (PC), Contemplation (C), Preparation (PR), Action (A), and Maintenance (M). Latent status is measured repeatedly over time and in the current study it is measured three times: at baseline, 12 months, and 24 months after baseline. The static part of LTA models does not change over time and is used to

divide the sample into groups. The variable in LTA associated with the static portion of the model is called latent class. Treatment group assignment is the static latent class in this study. The latent class division permits comparison of stage membership and stage transitions between two treatment groups.

LTA models involve five different types of parameters: 1) the gamma parameters (γ), which are estimates of the proportion of the population in each latent class, 2) the delta parameters (δ), which are estimates of the proportion of the population in each latent status at each occasion of measurement, conditional on latent class, 3) the tau parameters (τ) which are the conditional probabilities of transitioning from one latent status to another, 4) the rho parameters (ρ) for the dynamic latent status variable, which represent measurement error and are estimates of a particular item response conditional on latent status membership and 5) the rho parameters (ρ) for the static latent class variable, which represent measurement error, that are estimates of a particular item response conditional on latent class membership. The current study includes the first three types of parameters.

The gamma parameters represent the proportion in each latent class and in the current study are the proportion of the population in each of the two treatment groups. The delta parameters are the proportion of the population in each of the five latent statuses conditional on treatment group assignment. The delta parameters here reflect the proportion of the population in PC, C, PR, A, and M at each occasion for each treatment group. The tau parameter matrix is the transition

probability matrix representing the probabilities of transitioning to each of the latent statuses, or stages, at each time, conditional on stage at the previous occasion and latent class (treatment group). There is one tau matrix for each latent class and is in our example a 5×5 matrix. When movement among stages can be either forward or backward, there is a full probability matrix. The diagonal elements of the tau matrix represent stability, i.e., the proportion of individuals who remain in the same latent status on both occasions of measurement. The elements above the diagonal represent progression. These values represent the proportion of individuals who move forward to a new latent status on the second occasion. The elements below the diagonal represent regression, i.e., the proportion of individuals who move backward to a previous latent status on the second occasion.

Until recently LTA used the Estimation Maximization (EM; Dempster, Laird, & Rubin, 1977) algorithm to produce maximum likelihood estimates for latent transition models. The maximum likelihood solution, however, does not provide standard errors. Recent advances in the LTA software (Collins, Schafer, Hyatt, & Flaherty, in preparation; Hyatt, Collins, & Schafer, 1999; Brunner, & Schafer, 1997) now use an Empirical Bayes approach, using data augmentation (DA; Schafer, 1997) for obtaining standard error estimates. Standard error estimates are useful in two ways: they provide a measure of uncertainty for each parameter estimate and they allow for hypothesis testing. Significance tests for differences between parameter estimates are conducted on the DA estimates and standard errors.

Hypothesis testing of LTA parameters can be performed using differences of proportions or relative risk ratios. For differences in proportions, the null hypothesis of no difference is rejected if the confidence interval for the difference does not contain zero. The technical details of conducting hypothesis testing are found in Hyatt, Collins, & Schafer (1997).

Previous studies have applied LTA to stages of change for smoking cessation in the adult population (Chapter 2 and Chapter 3, this volume; Martin, Velicer & Fava, 1996, Velicer, Martin & Collins, 1996). In the first study, LTA was used to test three alternative models of transitions among the stages of change for smoking cessation (Martin, Velicer & Fava, 1996). The models assessed movement among the stages for a two-year period. The model that fit the data best indicates that in a six-month period both progression and regression among the stages takes place as well as two-stage progression. Examination of the probability of movement among the stages revealed three findings consistent with the Transtheoretical Model of behavior change. First, movement through the stages is not always linear. Second, the probability of forward movement is greater than backward movement. Third, the probability of moving to adjacent stages was greater than probability of two-stage progression.

In the second (Chapter 2, this volume) and third studies (Chapter 3, this volume) previous descriptive findings were replicated and the program of research was extended in two ways. First, LTA was applied inferentially to examine differential treatment effects for stage-matched expert system intervention versus

assessment control condition for smoking cessation in a sample of adult proactively recruited smokers. Second, analysis of stage transitions over time was examined as a process evaluation. The examination of the delta and tau parameter estimates demonstrated a strong intervention effect for the expert system intervention compared to the control conditions in both studies. The effects of the intervention were strongest for the early stages and declined over time. However, there was less of the population in the early stages at the later follow-up periods. The studies demonstrated utility of LTA as process analysis and the utility of LTA for detecting treatment effects descriptively. Several limitations were also demonstrated: evaluating alternate models and the potential for obscuring cumulative treatment effects due to lack of power and lack of sensitivity of data augmentation procedures.

The current study provides an empirical example of the application of LTA to the stages of change and smoking cessation among a population of parents of high school students undergoing intervention for multiple problem behaviors. The application of latent transition methodology to the stages of change will be informative on two levels: methodological and theoretical. First, because the stage of change model is well researched and understood, it provides a platform to which the strengths and limitations of the latent transition methodology may be studied. Therefore one can gauge the usefulness of LTA in contributing unique information to a well-studied phenomenon. Second, the applications to the stages of change will provide a more detailed picture of how people change over time as compared

to what is found using traditional data analytic techniques. The study will demonstrate the types of information obtained using LTA and the utility of LTA for examining group differences.

Method

This study is secondary analyses of data collected in a larger study (Prochaska et al., 2002b). The purpose of the larger study was to test a stage-matched home-based intervention program designed for parents of high-school adolescents that targeted three of the most important and most preventable risks of cancer morbidity and mortality: smoking, dietary fat and fiber, and sun exposure. Students' parents were assessed by phone and given stage-matched manuals and expert system feedback. In conjunction with this parent intervention, students were given a series of eight stage-matched, interactive expert system feedback sessions and received a school-based social influence curriculum. The school intervention targeted the same three risk factors. The school and home interventions were conducted simultaneously to assess the potential additive effects of treating both teenagers and their parents.

Procedure

A list of parents who had a ninth grader in the school study was provided by schools participating in the school-based health promotion study, and initial screening identified a total of 3,507 available households (i.e. households that could be reached by telephone). 2,931 respondents were contacted by phone. One parent was recruited from each eligible household. A total of 576 parents refused

participation. The overall recruitment rate was 83.6% of available parents who could be contacted. Eligibility requirements included being at risk for at least one of the three health behaviors targeted for intervention in the study. Of the 2,931 parents who agreed to participate, 471 (16.2%) were screened out because of not having at least one of the three behavioral risks, leaving a sample of 2,460 at-risk subjects.

The study design was a randomized 2X2X4 measurement occasions factorial design that crossed the school intervention with the home intervention with four follow-up assessment occasions (baseline, 12, and 24). The unit of assignment for the home intervention was the individual. Twenty-two high schools were selected from the 38 in Rhode Island. Within each school, half of the students' parents were assigned at random to the home-based expert system intervention ($N = 1,209$) or assessment-only conditions ($N = 1,251$). The current study will be limited to examination of the parent intervention for smoking up through and including the 24-month follow-up.

The baseline survey was used to determine if the subject was "at risk" for each of the three risk behaviors. At-risk status was defined as being in the Precontemplation, Contemplation, or Preparation stage of change for each risk behavior. Intervention was provided for each risk only when the subject was identified as at-risk (e.g., nonsmokers did not receive any intervention for smoking). Subjects in both groups were administered follow-up assessments at 12 and 24 months by telephone or mail survey. Those assigned to the expert system

treatment condition were mailed intervention materials for all risk behaviors for which they were identified as being at-risk. Mailed materials included the baseline feedback report and an integrated multiple risk behavior stage-matched self-help manual. The responses to the phone survey generated the expert system report for the intervention group. Subjects in the Assessment Only group were proactively assessed at twelve-month intervals.

At six and twelve months, treatment subjects were mailed a progress questionnaire. At baseline, 711 respondents were identified as smokers, 1,745 were identified as nonsmokers, and the information was missing for four respondents. Smokers completed the assessment necessary to generate the smoking cessation expert system progress report as part of the baseline assessment. Of the 711 smokers at baseline, 453 completed the 12 Month assessment (63.8%) and 409 completed the 24 Month assessment (58.0%).

Interventions

The expert system intervention involves a series of three computer reports at the start of treatment and at 6 and 12 months for each risk factor. The three to five page, single-spaced reports were divided into at least five sections for each risk behavior. The first section consists of a description of the person's stage of change and readiness to change their behavior. The second section described their pros and cons of changing and feedback, when necessary, about their under-evaluating the pros of changing and/or over-evaluating the cons for that behavior. It also includes comparisons at follow-up with prior evaluations. The third section

consists of feedback on their use of up to six change processes. They are compared normatively on each process with self-changers in the same stage of change who were most successful in progressing to the next stage. For the two follow-up assessments, they are compared ipsatively with their prior assessment. The fourth section consists of a description of tempting situations, with feedback on how to enhance their self-efficacy in their most tempting situations. The last consists of a section on strategies for taking small steps to progress to the next stage.

The progress reports also referred participants to the sections of an integrated multiple risk behavior stage-matched self-help manual that were most relevant to their individual progress. The manual entitled, *Pathways to Health: Promoting Health, Preventing Cancer*, provides more detail about each risk behavior and teaches users about their particular stage of change and the processes they can use to progress to the next stage (Prochaska, Redding, et al., 1995). The reports were mailed within 2 weeks of completion of their telephone survey or receipt of their mailed survey. More details about the expert system and manuals are available elsewhere (Velicer, Prochaska, Bellis, DiClemente, Rossi, Fava, & Steiger, 1993; Velicer, Rossi, Ruggeiro, & Prochaska, 1994).

Participants

The sample consisted of 2,461 adults. The sample was 24.7% male, 92% White, 2.6% Black, 3.4% Hispanic, .8% American Indian, and 1.3% Asian. The sample was 42 ($SD=5.55$) years old, 76.6% married, and had an average of 13 years of education. Of the parents, 1,511 were current or former smokers.

Nineteen and one-half percent were in Precontemplation, 19.5% were in contemplation, 8% were in Preparation, 5% were in Action, 48.9% were in Maintenance. Of the 711 smokers, 1% were in Precontemplation, 41% were in Contemplation and 18% were in Preparation.

Method of Analysis

The analysis was performed using WinLTA (Collins, Lanza, Schafer, & Flaherty, 2002). First, LTA was used to specify a model that best explains movement between the stages over time and to examine transitions between the stages. A model building approach was used in model testing where each subsequent model added transition probability parameters to the previous model. Five nested models similar to models in previous studies (Martin et al., 1996; Evers, Harolw, Redding, & LaForge, 1998) were compared for goodness of fit using double crossvalidation (Cudeck & Browne, 1983). Double crossvalidation involves identifying a set of plausible models, estimating parameters separately in each half of a randomly split sample, and computing the two fit indices by applying each model as fitted in one half to the opposite half of the sample. The crossvalidation fit indices are examined and the model with the best indices is selected. Figure 5 presents the five models. Model 1 proposes one stage forward movement. Model 2 proposes one stage forward and backward movement. Model 3 proposes one stage forward and backward movement and two stage forward movement. Model 4 proposes one stage forward and backward movement, two-stage forward movement, and two stage backward movement. Model 5 proposes

one stage forward and backward movement, two stage forward and backward movement, and three stage forward movement. Nested models are compared by subtracting the values of G^2 and associated degrees of freedom.

Second, delta parameter and tau parameter estimates are analyzed descriptively. The delta parameters provide information of how the stage membership (proportion of the population in each stage) changes over time. The tau parameters provide detailed information on the probability of transitioning from one stage to another conditional on treatment group and previous stage. Third, differential treatment effects are examined using data augmentation procedures to test a series of planned comparisons comparing delta and tau parameter estimates between treatment and control conditions. Fourth, an application of how LTA data can be examined as a process evaluation is provided.

The LTA routine for incomplete data was used so all cases could be employed at all time points. The procedure is based on computational techniques developed to handle missing data in contingency tables (Schafer, 1997) and is robust when the data are missing completely at random or missing at random (Hyatt & Collins, 1998).

Results

Overall Model Fit

Following the recommendation of Cudeck & Brown (1983) double crossvalidation procedures were used to specify models and compare model fit. The sample was randomly split into two samples, A and B, and parameter values

Figure 5

Five alternate nested models

Model 1

Model 2

Model 3

Model 4

Model 5

for each of the five models were estimated separately in each half and then fit indices were computed by applying each model as fitted in one half to the opposite half of the sample. Model one proposed one stage forward movement. Model two proposed one stage forward and backward movement. Model three proposed one stage forward and backward movement and two stage forward movement. Model four proposed one stage forward and backward movement, two-stage forward movement, and two stage backward movement. Model 5 proposed one stage forward and backward movement, two stage forward and backward movement, and three stage forward movement.

Only Model 1 converged without error. Model 2, Model 3, Model 4, and Model 5 failed to converge and crossvalidate because these models specified regression from Maintenance which could not be properly modeled given the observed data. Models 2 thru 5 were run fixing the Maintenance tau parameters such that probability of remaining in Maintenance was equal to 1.0. Table 13 displays the G^2 and degrees of freedom results of the double crossvalidation procedure for the five models. The results are presented for half the sample, labeled Sample A, and then for the other half of the sample, labeled Sample B. Results of the initial model estimation on each half of the sample are in the columns labeled Calibration G^2 . Results of each model as fitted in one half of the sample as applied to the opposite half are presented in the columns labeled Crossvalidation G^2 .

Table 13

Results of Crossvalidation on Sample Split Randomly into Samples A and B

		Sample A		Sample B	
		Calibration G^2 on A	Cross- Validation G^2 on B	Calibration G^2 on B	Cross- Validation G^2 on A
Model 1	G^2 df	281.54 225	313.36	288.64 225	315.16
Model 2	G^2 df	214.48 215	282.39	217.05 215	264.86
Model 3	G^2 df	143.76 203	220.62	114.82 203	187.70
Model 4	G^2 df	138.92 197	225.03	108.91 197	191.89
Model 5	G^2 df	73.96 189	173.98	71.52 189	178.58

Note. Model 1 proposes one stage forward movement. Model 2 proposes one stage forward and backward movement. Model 3 proposes one stage forward and backward movement and two stage forward movement. Model 4 proposes one stage forward and backward movement, two-stage forward movement, and two stage backward movement. Model 5 proposes one stage forward and backward movement, two stage forward and backward movement, and three stage forward movement.

Overall model fit for the five models is carried out by comparing model fit statistics using G^2 difference tests. G^2 difference tests are presented in Table 14. A nonsignificant value of G^2 difference suggests the overall fits of the two models are comparable. A significant result supports retaining the parameters added by the larger model. Assuming the G^2 difference is distributed as chi-square, the more restrictive models represent a significant decrement in model fit compared with the more general model. Model 3 was selected as the best fitting model because it cross validated best.

Gamma Parameter Estimates (Probabilities of Latent Class Membership)

The gamma parameters represent the proportion of the population in each of the two latent classes or in this case treatment groups. Forty-nine percent (95% CI .456-.529) of the population was in the intervention group and 51% (95%CI .471-.544) was in the control group.

Delta Parameter Estimates (Probabilities of Latent Status Membership)

The delta parameters are the proportion of the population in each of the latent statuses (e.g. stages) at each time conditional on latent class (e.g. treatment assignment). The delta parameter estimates and confidence intervals are presented in Table 15. It was hypothesized that at each follow-up the intervention group would have lower probabilities of being in the Precontemplation, Contemplation, and Preparation stages of change and have higher probabilities of being in the Action and Maintenance stages of change compared to the control group. There was mixed support for this hypothesis. At the 12-month follow-up the intervention

Table 14

Results of G^2 Difference Tests Comparing Nested Models on Sample Randomly Split into Samples A and B.

	Sample A		Sample B	
	G^2 difference	df	G^2 difference	df
Model 2-1	30.97	10*	50.30	10*
Model 3-2	61.77	12*	77.16	12*
Model 4-3	4.41	6	4.91	6
Model 5-4	51.05	8*	14.26	8

* $p < .001$

Table 15

Estimates and 95% CI of Delta (δ) Parameters, Probabilities of Latent Status Membership

	Baseline	12 months	24 months
<u>Precontemplation</u>			
Intervention	.428 [.422-.436]	.361 [.346-.377]	.396 [.380-.412]
Control	.382 [.373-.391]	.380 [.366-.393]	.345 [.332-.359]
<u>Contemplation</u>			
Intervention	.446 [.438-.454]	.386 [.364-.408]	.305 [.291-.320]
Control	.412 [.401-.422]	.381 [.359-.403]	.416 [.394-.438]
<u>Preparation</u>			
Intervention	.118 [.110-.125]	.106 [.086-.127]	.103 [.085-.120]
Control	.199 [.192-.207]	.151 [.113-.169]	.111 [.102-.121]
<u>Action</u>			
Intervention	.0	.139 [.127-.150]	.152 [.132-.172]
Control	.0	.082 [.072-.093]	.119 [.109-.129]
<u>Maintenance</u>			
Intervention	.0	.004 [.002-.006]	.040 [.035-.045]
Control	.0	.002 [.001-.002]	.004 [.002-.006]

Note. A value of .0 indicates that the parameter was fixed at zero.

group has a lower proportion in Precontemplation (.361) compared to the control group (.380) but a slightly higher proportion in Contemplation (.386) compared to the control group (.381). At the 24-month follow-up the intervention group has a higher proportion in Precontemplation (.396) compared to the control group (.345) but a lower proportion in Contemplation (.305) compared to the control group (.416). At both the 12-month and 24-month follow-ups the intervention group has a lower proportion in Preparation (.106 at 12 months and .103 at 24 months) compared to the control group (.151 at 12 months and .111 at 24 months).

At both the 12-month and 24-month follow-ups the intervention group has a higher proportion in Action (.139 at 12 months and .152 at 24 months) and Maintenance (.004 at 12 months and .04 at 24 months) compared to the control group (for Action .082 at 12 months and .119 at 24 months and for Maintenance .040 at 12 months and .004 at 24 months).

It was also hypothesized that the proportion in Precontemplation, Contemplation, and Preparation would decrease over time and that the membership in Action and Maintenance would increase over time. The results for the intervention group support this hypothesis with one exception. The proportion in Precontemplation decreases from .428 at baseline to .361 at 12 months and then increases to .396 at 24 months. The proportion in Contemplation decreases over time from .446 to .386 to .305. The proportion in Preparation decreases over time from .118 to .106 to .103. The proportion in Action increases from .139 at 12

months to .152 at 24 months. The proportion in Maintenance increases from .004 at 12 months to .04 at 24 months.

The results for the control group support the hypothesis except for the proportion in Contemplation that increases at 24 months. The proportion in Precontemplation decreases over time from .382 to .380 to .345. The proportion in Contemplation decreases over time from .412 at baseline to .381 at 12 months and then increases to .416 at 24 months. The proportion in Preparation decreases over time from .199 to .151 to .111. The proportion in Action increases from .082 at 12 months to .119 at 24 months. The proportion in Maintenance is approximately the same at 12 (.002) and 24 months (.004).

While the pattern of delta parameter value over time is similar between the intervention and control groups, the magnitude of the values differs. The Action stage membership increases to 14% at 12 months for the intervention group compared to only 8% for the control group. The Maintenance stage membership increases to 4% at 24 months for the intervention group compared to less than 1% for the control group.

Some interesting group differences emerged. In a later section, hypothesis tests will be conducted to see if the differences are statistically significant.

Tau Parameter Estimates (Probabilities of Latent Status Transitions)

A specific interest of this study is the difference between the intervention group and control group in overall transitions among the stages of change. The tau parameters represent the conditional probability of transitioning to a particular

Table 16

Estimates and 95% CI of Tau (τ) Parameters, Probabilities of Latent Status Transitions

Baseline Stage of Change	12 Month Stage of Change				
	PC	C	PR	A	M
<u>Intervention Group</u>					
Precontem- plation	.713 [.572-.819]	.261 [.159-.393]	.027 [.001-.286]	.0	.0
Contem- plation	.125 [.061-.234]	.524 [.416-.622]	.116 [.056-.223]	.235 [.156-.336]	.0
Preparation	.0	.343 [.153-.584]	.359 [.130-.653]	.277 [.092-.567]	.020 [.001-.315]
Action	.0	.0	.0	1.000	.0
Maintenance	.0	.0	.0	.0	1.000
<u>Control Group</u>					
Precontem- plation	.827 [.695-.906]	.102 [.035-.246]	.071 [.019-.215]	.0	.0
Contem- plation	.155 [.070-.298]	.622 [.475-.743]	.089 [.030-.223]	.135 [.077-.227]	.0
Preparation	.0	.435 [.297-.573]	.434 [.258-.617]	.131 [.047-.306]	.001 [.000-.099]
Action	.0	.0	.0	1.000	.0
Maintenance	.0	.0	.0	.0	1.000

Table 16 (continued)

12 Month Stage of Change	24 Month Stage of Change				
	PC	C	PR	A	M
<u>Intervention Group</u>					
Precontem- plation	.914 [.507-.994]	.039 [.001-.353]	.047 [.002-.400]	.0	.0
Contem- plation	.168 [.057-.379]	.665 [.503-.790]	.096 [.004-.590]	.072 [.014-.259]	.0
Preparation	.0	.318 [.071-.706]	.376 [.093-.748]	.282 [.050-.698]	.024 [.002-.311]
Action	.0	.0	.064 [.004-.472]	.678 [.473-.825]	.254 [.107-.483]
Maintenance	.0	.0	.0	.0	1.000
<u>Control Group</u>					
Precontem- plation	.782 [.668-.860]	.212 [.126-.329]	.007 [.000-.120]	.0	.0
Contem- plation	.127 [.063-.239]	.651 [.476-.797]	.163 [.064-.341]	.053 [.004-.316]	.0
Preparation	.0	.565 [.199-.871]	.278 [.054-.678]	.155 [.020-.544]	.002 [.001-.146]
Action	.0	.0	.057 [.002-.465]	.897 [.574-.987]	.046 [.003-.352]
Maintenance	.0	.0	.0	.0	1.000

Note. A value of .0 indicates that the parameter was fixed at zero.

Figure 6

Tau parameter estimates. Intervention group estimates are marked in italics type and control group estimates are in parentheses.

stage of change given the previous stage of change and the treatment group assignment. The tau parameter estimates and the associated 95% confidence intervals are presented in matrix form in Table 16. Figure 6 displays the tau parameter estimates graphically. Examination of the tau parameter matrices in Table 16 provides very detailed information regarding the probability of transitioning from one stage of change to another (conditional on previous stage of change and treatment group). The cells above the diagonal indicate advancement in stage, or progression. The cells along the diagonal indicate no change in stage, or stability. The cells below the diagonal indicate returning to a previous stage, or regression.

Several general observations can be made about the pattern of the transition probabilities. First, the probability of transition to adjacent stages was greater than nonadjacent stages. Although two-stage progression or regression within a twelve-month period is possible, it is more probable to transition to the next stage. The probability of two-stage progression for Precontemplation is .002 at its lowest (for the control group at 12 months) and .071 at its highest (for the control group at baseline). The probability of two-stage progression for Contemplation is .053 at its lowest (for the control group at 12 months) and .236 at its highest (for the intervention group at baseline). The probability of two-stage progression for Preparation is .001 at its lowest (for the control group at baseline) and .025 at its highest (for the intervention group at 12 months). Second, for two stages, Precontemplation and Contemplation, the probability of remaining in the same

stage from one time point to the next was greater than the probability of transitioning to all other stages combined. The probability of remaining in Precontemplation for the intervention group was .713 from baseline to 12 months and .914 from 12 months to 24 months. The probability of remaining in Precontemplation for the control group was .827 from baseline to 12 months and .782 from 12 months to 24 months. The probability of remaining in Contemplation for the intervention group was .524 from baseline to 12 months and .665 from 12 months to 24 months. The probability of remaining in Contemplation for the control group was .622 from baseline to 12 months and .657 from 12 months to 24 months.

Third, the probability of transitioning is the highest for the Preparation stage. From baseline to 12 months the probability of remaining in Preparation is .359 for the intervention group and .434 for the control group. From 12 months to 24 months the probability of remaining in Preparation is .376 for the intervention group and .278 for the control group.

It was hypothesized that the probability of progression would be greater than regression for any stage across both the intervention and control groups. The probability of progression is calculated by summing transition probabilities above the diagonal element for each stage. The probability of regression is calculated by summing the transition probabilities below the diagonal element for each stage. This hypothesis was supported in both the intervention group and the control group except for the Preparation stage, which consistently had greater regression than

progression. For the intervention group the probability of progression was greater than regression for Contemplation from baseline to 12 months (.351 vs. .125) and about the same from 12 months to 24 months (.169 vs. .168). For the control group the probability of progression was greater than regression for Contemplation from baseline to 12 months (.224 vs. .155) and 12 months to 24 months (.216 vs. .127). For the intervention group the probability of progression was greater than regression for Action from 12 months to 24 months (.254 vs. .064). For the control group the probability of progression was not greater than regression for Action from 12 months to 24 months (.046 vs. .057). For the intervention group the probability of regression was greater than progression for Preparation from baseline to 12 months (.297 vs. .343) and about the same from 12 months to 24 months (.306 vs. .318). For the control group the probability of regression was greater than progression for Preparation group from baseline to 12 months (.132 vs. .435) and 12 months to 24 months (.157 vs. .165).

It was also hypothesized that the intervention group would experience less regression and more progression among the stages compared with the control group. This hypothesis, too, was supported. At baseline, for Precontemplation, the probability of progressing is higher in the intervention group (.288) than the control group (.173). At 12 months, the probability of progressing is lower in the intervention group (.086) than in the control group (.217). At baseline, for Contemplation, the probability of progressing is higher in the intervention group (.351) than the control group (.224) and the proportion regressing is lower in the

intervention group (.125) than the control group (.155). At 12 months the probability of progressing is lower in the intervention group (.168) than in the control group (.216), and the probability of regressing is higher in the intervention group (.168) than the control group (.127). For Preparation, at both baseline and 12 months, the probability of progressing is higher in the intervention group (.317 at baseline and .306 at 12 months) than the control group (.132 at baseline and .157 at 12 months), and the probability of regressing is lower in the intervention group (.343 at baseline and .318 at 12 months) than the control group (.435 at baseline and .565 at 12 months). For the Action, stage the probability of progressing is higher in the intervention group (.254) than the control group (.046), but the probability of regressing is lower in the control group (.057) than the intervention group (.064). Overall, there is a strong pattern in the progression and regression statistics that indicate the intervention group has better outcomes compared with the control group.

Results of Tests of Hypotheses

Tests of significance were conducted to examine hypotheses about group differences in delta parameters and the tau parameters. Results from these tests based on the differences of proportions are presented. For differences of proportion, the null hypothesis of no difference is rejected if the confidence interval for the differences does not contain zero.

Several tests of delta parameters reach statistical significance as shown in Table 17. At 24 months, those in the intervention group are significantly less likely

to be in Contemplation ($\delta = .305$) compared with the control group ($\delta = .416$) and also, those in the intervention group are significantly more likely to be in Maintenance ($\delta = .040$) compared with the control group ($\delta = .004$).

Several tests of the tau parameters reached significance. Table 18 presents the differences of proportions and 95% CI for the tau parameters. One difference in proportions is significant from baseline to 12 months. The probability of progressing from Precontemplation to Contemplation is higher for the intervention group ($\tau = .261$) than for the control group ($\tau = .102$). Three differences in proportions are significant from 12 months to 24 months. The probability of progressing from Precontemplation to Contemplation is lower for the intervention group ($\tau = .039$) than for the control group ($\tau = .210$). From 12 months to 24 months the probability of progressing from Action to Maintenance is higher for the intervention group ($\tau = .254$) than for the control group ($\tau = .046$). From 12 months to 24 months the probability of remaining in Action is higher for the control group ($\tau = .897$) than for the intervention group ($\tau = .681$).

Process Evaluation

The purpose of the process evaluation is to identify when and for what stages of change the intervention is most effective by examining the delta and tau parameters over time. The delta parameters represent the growth and decline of stage membership over time. What is shown in the pattern of delta parameters is that the intervention group reduces membership in the early stages of Contemplation and Preparation and increases membership in the late stages of

Table 17

Hypothesis Testing: Difference of Proportions and 95% CI for Delta (δ) Parameters

	Baseline	12 Months	24 Months
Precontemplation	.047 [-.030-.123]	.018 [-.065-.101]	.051 [-.051-.152]
Contemplation	.034 [-.047-.116]	.005 [-.103-.112]	.111* [.016-.206]
Preparation	.082* [.019-.144]	.045 [-.046-.135]	.008 [-.064-.080]
Action	--	.056 [-.002-.114]	.033 [-.045-.111]
Maintenance	--	.002 [-.008-.012]	.036* [.008-.064]

* $p < .05$

Table 18

Hypothesis Testing: Differences of Proportions and 95% CI for Tau (τ) Parameters

Baseline Stage of Change	12 Month Stage of Change				
	PC	C	PR	A	M
Precontem- plation	.114 [-.027-.256]	.159* [.032-.286]	.045 [-.046-.135]	--	--
Contem- plation	.030 [-.069-.129]	.098 [-.071-.267]	.027 [-.074-.129]	.100 [-.006-.207]	--
Preparation	--	.091 [-.144-.328]	.075 [-.210-.359]	.146 [-.112-.404]	.020 [-.056-.096]
12 Month Stage of Change	24 Month Stage of Change				
	PC	C	PR	A	M
Precontem- plation	.132 [-.009-.272]	.171* [.036-.306]	.040 [-.044-.123]	--	--
Contem- plation	.040 [-.102-.182]	.008 [-.195-.211]	.067 [-.069-.203]	.019 [-.114-.152]	--
Preparation	--	.247 [-.273-.767]	.098 [-.310-.506]	.127 [-.185-.440]	.022 [-.061-.105]
Action	--	--	.022 [-.122-.166]	.245* [.002-.488]	.211* [.025-.422]

* $p < .05$

Action and Maintenance. The intervention group has lower proportions in the early stages compared with the control group and higher proportions in the late stages except for Precontemplation at 24 months. Not only is the stage membership in Contemplation and Preparation stages lower for the intervention group it declines over time and the membership in the late stages higher for the intervention group grows over time. The effects on Precontemplation appear to fade by 24 months as evidence by the increases in stage membership for the intervention group and the greater proportion in Precontemplation for the intervention group compared with the control group.

Examination of the pattern of tau parameter values also provides valuable information about when and for which stages of change the intervention is most effective. The tau parameters are evaluated *between groups* and *over time*. A favorable *between groups* outcome for the intervention group is marked by higher probabilities of progressing one or two stages compared to the control group. It is likely that if there is higher probability of progressing within the stages the probability of regressing back one or two stages is lower. From baseline to 12 months, the intervention group outperforms the control group for all stages. From 12 months to 24 months, the effects appear more moderate and are divided by late and early stages. For the early stages, the control group outperforms the intervention group. For the late stages, the intervention group outperforms the control group. The intervention appears to assist those in Action to transitioning to Maintenance. For someone in Action the probability of maintaining the quit at

least six months is almost 25% with the expert system intervention versus less than 5% without the intervention.

A favorable outcome for the intervention group *over time* is marked by the transition probabilities decreasing for the regression parameters and increasing for the progression parameters. The favorable outcome effects for the Precontemplation and Contemplation stages appear to decline by 12 months. From 12 to 24 months, the probabilities of remaining in Precontemplation and Contemplation increase and the probabilities of progressing decrease. For someone in Precontemplation at 12 months the probability of remaining in Precontemplation is high. The favorable outcome effects for the Preparation and Action stages are sustained through 24 months.

The delta parameter and tau parameter information taken together provide another level of information than either of the parameters alone. The consistency of the delta parameter results is remarkable. The membership in the early stages is lower and continues to decline and the membership in the late stages is higher and continues to increase for the intervention group compared to the control group with the exception of Precontemplation. Therefore the transition probabilities (tau parameter) for the early stages are applicable to a declining membership, and the transition probabilities for the late stages are applicable to growing membership. In other words, the denominator for the transition probability, the proportion in a particular stage at a particular time, is decreasing for the Contemplation and Preparation and increasing for the late stages in the intervention group. Although

the effects of the intervention for the early stages decline over time, there is less of the population in the Contemplation and Preparation stages 12 and 24 months after the intervention. This intervention with the Precontemplators appears to weaken over time. The intervention was delivered at baseline, 6months and 12months. By 24 months the effects of the intervention are gone. It would be interesting to know the status of the Precontemplators at 18 months (which would be 6 months post intervention). Perhaps the results at 18 months would be similar to the 12 month results.

Discussion

The results of this study provide information about latent transition methodology and the application of this methodology to the stages of change for smoking cessation in a population of high school parents. The study examined model specification, the pattern of parameter values, statistical tests for treatment group differences, and the application of LTA as a process analysis. The type of information obtained using LTA and the utility of LTA for examining group differences was demonstrated.

Examination of the parameter estimates generated by LTA demonstrates a pattern of results that is somewhat consistent with the results of Chapter 2 and Chapter 3. The delta estimates, representing the proportion of the population in each stage at each time point conditional on treatment group, differed between the intervention group and control group. The delta parameters show that the intervention group has higher proportions in Action and Maintenance compared to

the control group. This suggests that the expert system intervention is effective at helping people to make a cessation attempt and in some instances maintain the quit. A greater number of subjects were engaged in attempts to quit smoking in the intervention group; hence, the greater increase in Action and Maintenance stage membership. The proportions in Precontemplation and Contemplation were not lower for the intervention group compared with the control group as was seen in Chapter 2 and Chapter 3. This finding suggests that in this population of parents the delta parameters for the early stages were similar for the two groups.

The tau parameter pattern indicates an intervention effect especially at the earliest follow-up period. There is less regression to an earlier stage and more progression to a later stage in the intervention group from baseline to 12 months. However, the magnitude of the effect decreases over time and diminishes for the Precontemplation and Contemplation stages by 24 months. In the case of this study, the intervention was administered at baseline, six months, and twelve months so the effects are larger at twelve months. The results of the process analysis were consistent with treatment having a greater effect more proximal to its delivery. Overall, the tau parameters over time were similar to Chapter 2 and Chapter 3, but the pattern tau parameters between the treatment groups differed especially for the early stages.

Although movement between the stages is very dynamic, results presented here indicate that smokers and former smokers are more likely to transition to the nearest stage as found in previous studies (Chapter 2 and Chapter 3, this volume;

Martin, Velicer, & Fava, 1996). Two-stage progression is less probable than moving to adjacent stages. This observation has implication for intervention design. It had previously been suggested that targeting stage-matched interventions at helping smokers progress one stage would be beneficial to smokers.

The transition probability estimates provide a detailed look at movement among the stages of change conditional on previous stage and treatment group. This allows for a very in depth examination of movement among the stages. This level of specificity, however, obscures the cumulative effect that there may be in two ways. First, typical point prevalence combines the Precontemplation, Contemplation, and Preparation stages and compares this proportion to the proportion in Action and Maintenance combined. The difference tested with a point prevalence estimate will be larger than the conditional proportions being compared within LTA. Second, point prevalence examines outcome at only one follow-up period. LTA results provided a detailed picture at each of several follow-up periods. Therefore, the cumulative effect seen with point prevalence is divided up among the two follow-up periods. At the earliest follow-up, the tau parameters reveal that the control group is more likely to remain in the current stage. Further, among those who transition out of the current stage, it is more likely that they will transition to an earlier stage of change. This suggests that LTA methodology is able to demonstrate intervention effects earlier than with point prevalence outcomes.

A model building approach was used in model evaluation where each subsequent model added transition probability parameters to the previous model. The model that specified two-stage forward and one-stage backward movement, Model 3, was selected as the best fitting model. The model evaluation results differ from the previous studies of Chapter 2 and Chapter 3 where Model 4 was retained as the best fitting model. Model 4 permits two-stage regression where Model 3 does not. It is unclear why Model 3 fit this population data better than Model 4. The major design difference between the studies is the time frame for measurement. In the current study there is a 12month time frame and in the Previous chapters there was a 6 month time frame.

This study has served two broad purposes. First, it has demonstrated the utility of latent transition methodology for the study of change. Several strengths of the method have been demonstrated: estimation of latent status membership, estimation of latent transition probabilities, and the utility of using LTA as a process analysis. Several limitations of the method have been demonstrated: testing alternate models, the potential obscuring of cumulative treatment effects found with traditional methods, and the lack of sensitivity of data augmentation procedures for testing group differences. Second, this study has demonstrated the utility of employing stage of change as an outcome measure. Stage membership is sensitive to change for all smokers, not just those achieving Action criteria. A comparison of tau parameter estimates for the treatment groups revealed that the

expert system provided in this study had a an impact on smoking in the entire population of high school parents.

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Chapter 5

General Discussion

Three secondary data analysis studies were conducted to provide empirical examples of the application of Latent Transition Analysis to three studies of smoking cessation among adults. Each study was designed to evaluate a stage-matched interactive expert system for smoking cessation in three different populations of smokers. The first study evaluated the expert system intervention versus assessment only controls in a population of smokers from the state of Rhode Island. The second study evaluated the expert system intervention versus a non-interactive manual-based intervention in a managed care setting. The third study evaluated the expert system intervention versus assessment only controls in a population of high school parents who were receiving interventions for up to three problem behaviors simultaneously. LTA in each study consisted of four parts: model specification, descriptive analyses of LTA parameter estimates, test of differential treatment effects using data augmentation procedures, and a descriptive process analysis. The studies were designed to be theoretically meaningful in evaluating the interactive expert system intervention and the use of stage of change as an outcome. The studies were designed to be methodologically meaningful by demonstrating the types of information obtained using LTA, the utility of LTA for examining group differences statistically using data augmentation procedures, and the utility of LTA as a process analysis.

Major Findings

The findings of the three studies will be discussed relative to each other in terms of the similarity and dissimilarity of their findings. For ease of presentation and discussion Chapter 2 is called random digit dial (RDD) study, Chapter 3 is called health maintenance organization (HMO) study, and Chapter 4 is called Parent study. The studies will be compared for model fit and the major hypotheses evaluated for the delta and tau parameters.

The three studies differ in important design features that may potentially impact the interpretation of the results as discussed here. The RDD study had five measurement periods at six month intervals with a sample size of 4,144. The expert system intervention (ESI) was delivered at baseline, 3 months and 6 months and was compared to assessment only. The HMO study had four measurement periods at six month interval with a sample size of 2,882. The expert system intervention (ESI) was delivered at baseline, 3 months and 6 months and was compared to a non-interactive manual based intervention. The Parent study had only three measurement periods at twelve month intervals with a sample size of 711 smokers. The expert system intervention (ESI) was delivered at baseline, 6 months, and 12 months and was compared to assessment only. The participants in the Parent study were receiving intervention for up to three behaviors simultaneously.

The model specification and selection was similar for the RDD and HMO populations. Model 4 was selected as the best fitting model. Model 4 permitted

both two-stage forward and backward movement. The Parent study differed in model selection. Model 3 fit the Parent data best. Model 3 permitted one-stage and two-stage forward movement and one-stage backward movement (except Maintenance). It is unclear why a longer time frame would result in the pattern of change found in the tau parameters, but this is worth considering.

Any measurement point captures the stage for a participant at that particular moment in time. Therefore, it is not accurate to assume that the transition to the stage at measurement is only stage transition that occurs between measurements. The six month time interval appears to be appropriate for finding effects for the PC and C stages of change but may be too long for PR and A. PR and A have a time parameter in their definitions. For Preparation there is a 30 day period specified, and Action is less than six months of abstinence. It would be interesting to see results for the tau parameters if a shorter time frame, 2 months for example, were used.

The delta parameters show the probability of latent status membership. There were two hypothesized patterns for the delta parameters. The first hypothesis examined the pattern of delta parameters over time. It was hypothesized that membership in Precontemplation, Contemplation, and Preparation would decrease at follow-up, and membership in Action and Maintenance would increase at follow-up. Overall, the membership in Precontemplation and Contemplation show a decline over time while Action and Maintenance show increased membership. The manner in which the proportions change was largely consistent

with the transition probabilities. Table 19 shows the results for this hypothesis across the three studies.

The second hypothesis examined the pattern of delta parameters between treatment groups. It was hypothesized that the ESI group would have lower proportions in Precontemplation and Contemplation at follow-up compared to the control group, and that the ESI group would have higher proportions in Action and Maintenance at follow-up compared to the control group. A greater number of subjects were engaged in attempts to quit smoking in the expert system intervention groups. Table 20 shows the results for this hypothesis across the three studies. Overall, the delta parameter estimates demonstrate the intervention's effects even when compared to a non-interactive intervention (HMO) and in a population experiencing simultaneous interventions for up to three problem behaviors (Parent study).

There were two hypothesized patterns for the tau parameters. The first hypothesis examined the pattern of tau parameters over time. It was hypothesized that the probability of progression would be greater than regression. Overall, there was more progression and less regression among the stages. This was especially true for the expert system intervention groups. These effects were demonstrated even in the early stages. Table 21 shows the results for this hypothesis across the three studies. This suggests that using stage of change as an outcome and examining the transitions between the stages provides meaningful information to which traditional outcome measures would not be sensitive.

Table 19

Comparison of Delta Parameter Results Over Time for RDD, HMO, and Parent Studies

Study	Proportion in PC, C, PR Decrease	Proportion in A & M Increase
RDD	Supported Except PC at 24 months for ESI	Supported Except A at 18 months for control
HMO	Supported Except PC at all times for control	Mixed Support Not supported for A
Parent	Supported Except PC at 24 months for ESI Except C at 24 months for control	Supported

Table 20

Comparison of Delta Parameter Results Between Treatment Groups for RDD, HMO, and Parent Studies

Study	Proportion in PC & C lower for ESI group compared to control group	Proportion in PR, A, M higher for ESI compared to control group
RDD	Supported	Supported
HMO	Supported Except C at 6 months	Supported Except PR at 12 & 18 months where they are the same
Parent	Supported Except PC at 24 months Except C at 12 months	Supported

Table 21

Comparison of Tau Parameters Over Time for RDD, HMO, and Parent Studies

Study	Probability of Progression greater than regressing
RDD	ESI – Supported except PR Control – Supported except PR, C from baseline-6 months
HMO	ESI – Supported except PR, C from 6-12 months Control - Supported except PR, C from 6-12 months
Parent	ESI- Supported except PR Control - Supported except PR

The second hypothesis examined the pattern of tau parameters between the treatment groups. It was hypothesized that the probability of progression would be greater for the ESI group compared to the control group and the probability of regression would be lower for the ESI group compared to the control group. Table 22 shows the results for this hypothesis across the three studies. The intervention effects for the early stages of change appear to become more moderate over time when compared to the control group, particularly for progression.

The transition probabilities also revealed findings consistent with a published study that applied LTA to the stages of change for smoking (Martin, Velicer, & Fava, 1996). Table 23 shows the replication of these results. Although movement between the stages is dynamic, smokers and former smokers are more likely to transition to the nearest stage. This observation has implication for intervention design. Targeting stage-matched interventions at transitioning smokers to progression one stage would capture a high proportion of the population, as is true with the expert system. These results indicate that there is systematic characteristic to the way smokers change their behavior.

A second finding which replicated was that the stability of stage membership was highest for Contemplation and Maintenance. Former smokers who have been abstinent for more than six months are more likely to remain in Maintenance than cycle back to an earlier stage. The Parent study demonstrates this point well. In the Parent study, models would not converge that modeled regression from Maintenance. The best fitting model was one that did not permit

Table 22

Comparison of Tau Parameters Between Groups for RDD, HMO, and Parent Studies

Study	Probability of Regression Lower for ESI compared to Control	Probability of Progression greater for ESI compared to Control
RDD	Supported Except PR from 6-12 months and M from 12-18 months	Supported Except PR from 6-12 months
HMO	Supported Except Maintenance	Mixed support Not supported for PC from 6-12 mos., C from 6-12 mos. and 12-18 mos., and PR from 12-18 months
Parent	Supported Except C from 12-18 months	Supported Except PC from 12-24 months and C from 12-24 months

Table 23

Comparison of RDD, HMO and Parent Studies Replication of Previously Published Findings

Study	Probability of Transition to Adjacent Stage greater than Non-Adjacent Stage	Stability of PC, C, & M
RDD	Supported	Supported
HMO	Supported	Supported
Parent	Supported	Supported for PC and C

movement from Maintenance. Former smokers who quit within six months appear to quickly move out of Action. The instability Action is indicative of the risk for returning to smoking. However, the likelihood of remaining abstinent from smoking was greater than the probability of returning to smoking, especially in the intervention conditions.

The utility of LTA for testing group differences using data augmentation procedures was not as strong as expected for two reasons. First, the procedure for testing group differences is completed outside of the LTA program and is complex, not straight-forward, and leaves room for potential researcher error. The data augmentation procedures provide imputed data sets from which estimates of error variance are calculated by the user. The imputed data sets produced by the DA procedure are combined based on the rule of Rubin (1987). This rule combines differences of proportions and the associated within-imputation variances across the imputed data sets to estimate the average point estimate, the overall amount of variance, and 95% CI for each interested statistic. This allows for the comparison of parameter estimates within and between groups. The procedures to get the end-result require extensive data management and programming in a statistical package.

Second, the procedures for testing differences of proportions were not sensitive to the differences between the groups. The reason for the insensitivity may be two-fold. First, the level of specificity of the probability estimates provided with LTA may obscure the cumulative effect that may exist. The overall difference of proportions is tested for a small portion of the entire sample. The conditional

probabilities by definition are contingent upon latent class and status and, therefore, what may be large treatment effects are essentially divided among the latent transition probabilities. Second, is the possibility that the differences between the groups is small, would have a very small effect size, and lack sufficient power to detect the effects. The original studies were powered to discover treatment effects in a certain range of potential outcomes, specifically for the proportion of the population moving into the Action and Maintenance stages at follow-up. Typically this is a small proportion of the sample, so the proportions are closer to zero than .50. Power is greater for any specified difference between proportions when the proportions are closer to zero than when they are closer to .50 (e.g., .10 vs. .20 is a larger difference, leading to more power, than a difference of .40 vs. .50). When examining unrestricted stage transitions, the proportions are likely to be higher than the proportions the studies original were powered to detect.

The utility of LTA for testing alternate models for the stages of change was not as strong as expected. The statistical comparisons of the five nested models using the G^2 difference tests did not provide meaningful results. With one exception, the G^2 difference tests were statistically significant indicating support for retaining the more general model. The absolute magnitude of the change in the parameter estimates added was small in all cases. It may be that the significance is due to large sample sizes rather than to the effect size (Kline, 1998). Another alternative is that the G^2 was not distributed as a chi-square so overall hypothesis testing of nested models is not possible (Collins, Fidler, Wugalter, & Long, 1993).

Alternate fit indices are needed to provide additional information for testing differences between models. A comparative fit index or R^2 statistic would be appropriate alternatives and could potentially be calculated. A null model would be specified where the progression and regression transition probabilities would be fixed to zero. Once a null model is specified, the comparative fit index and R^2 would be calculated. Multiple fit indices would be a contribution to the model evaluation component on LTA.

The studies presented here present the most complex LTA models in the published literature and information available at the WIN LTA web-site. The RDD study had the most extensive models combining a high number of latent statuses and number of time points. The missing data routine was also employed adding to the complexity. Run time for LTA varied widely for the studies presented and ranged from seconds for the Parent study to almost 60 hours for the RDD study. Running LTA models can be lengthy and is computer resource intensive. When running the LTA program it is not efficient to be running other programs simultaneously. Even word processing can lag when LTA is running. This is particularly true when running DA to obtain imputed data sets which can take thousands to tens-of-thousands iterations. At times LTA was difficult to converge, particularly in the Parent study. The complexity of the conducting the data augmentation procedure taken with the considerations presented here indicate that while the LTA interface is easy to use some aspects of the methodology are complex.

Recommendations for Future Research

Future research in this area is necessary to expand upon the results and continue to contribute to our knowledge of LTA and the stages of change. The conditional probabilities of latent status transitions ($\tau_{i,j}$) were contingent upon latent class and latent status at the previous measurement period. These are considered first-order models. It is possible to run second-order LTA models where the latent status transitions are contingent upon latent status at the two previous measurement periods. This would provide another level of detail and would be particularly useful for examining the early stages of change where stability appears to increase over time.

A second future direction for LTA and stages of change research would be to model two stage-sequences (Flaherty & Collins, 1999). Modeling two stage-sequences would provide a description of the impact of one's memberships in one stage sequence on their membership in another stage sequence. This would be particularly useful for studies examining simultaneous interventions for several problem behaviors. It would also be useful for examining the effect of one stage sequence on a second. Theoretically, this is very interesting in the area of the addictions, particularly smoking, where the use of one substance is strongly related to use patterns in a second substance (e.g., tobacco and alcohol). Modeling two stage-sequences can answer questions like "does an individual's stage of change for tobacco predict the stage of change for alcohol use?" and "does change in one's stage of change for tobacco predict change in stage of change for alcohol?". While

modeling two stage-sequences is in its infancy it is worth considering. It would be useful to model relations and changes among two stage-sequences.

A future direction for LTA specific to the LTA methodology is to advance the model evaluation component. As discussed above alternate fit indices are needed to provide additional information for model evaluation. The development and evaluation of model fit indices will be an important contribution to the methodology.

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