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BEYOND POPULATION LEVEL EFFECTS: ADDRESSING SAMPLE HETEROGENEITY IN PREVENTION RESEARCH

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Abstract

The unifying theme of my three-paper dissertation was the examination of inter-individual differences using two general methods for illustrating heterogeneity in a sample: mixture models and person-specific analysis. Study 1 examined issues of estimation, classification, and parameter recovery in non-identified latent class models that *appear* identified (i.e., positive df and model convergence). A model was simulated that was known to be non-identified (4 indicators – 3 classes), and these models were found to often provide interpretable solutions that do not represent the true population model, which resulted in high misclassification of individuals and poor parameter recovery. Study 2 used group-level and person-specific Markov models to examine the pattern of indoor tanning over time, as well as the extent to which current and previous day weather conditions affect this pattern. Results indicated that there was substantial heterogeneity across individuals in patterns of tanning over time. In addition, there appeared to be no relationship between weather conditions and the probability of transitioning to the "Tanning" state from the "No Tanning" state when examined at the group-level and in the majority of person-specific analyses. Study 3 evaluated the efficacy of an intervention aimed at reducing indoor tanning and examined potential heterogeneity in this tanning over time. Results indicated that the intervention was successful at decreasing indoor tanning across the length of the study, and that there were three patterns of tanners among the treatment individuals: abstainers, moderate tanners, and heavy tanners. The intervention was shown to have a harm reduction effect by reducing levels of exposure within the moderate and heavy tanner classes. Substantive and methodological contributions to the field were discussed for each study, as well as for the dissertation as a whole.

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General Introduction

Beyond population level effects: Addressing sample heterogeneity in prevention research

While measures of central tendency represent the foundation of statistical analysis in the behavioral sciences, they are not sufficient to portray a distribution. An average value can be highly descriptive of a sample, but the mean can be largely meaningless unless it is discussed in the context of sample variability. The same can often be said of more inferential parameter values (e.g., regression coefficients). These types of parameters describe the *average* associations between variables in a given sample or population. Throughout the behavioral sciences, a wealth of examples exists where the average results from a population are not sufficient to completely describe a phenomenon of interest (for example: Chung & Martin, 2001; Coffman et al., 2007; Dierker et al., 2006; Lanza, Collins, Lemmon, & Schafer, 2007; Muthén & Muthén, 2000; Rovine, Molenaar, & Corneal, 1999; Rovine & Walls, 2006; Russell, Jones, & Miller, 2007), such that attention must be paid to inter-individual differences. The unifying theme of my three-paper dissertation was the examination of these inter-individual differences using two general methods for illustrating heterogeneity in a sample: mixture models and person-specific analysis. The following sections will provide overviews of these two analytic strategies.

Mixture Models

The foundation of mixture modeling can be found in the work of Pearson near the end of the 19th century (1894). Based on the ratios of forehead to body length measurements of 1000 sea crabs, Pearson illustrated that modeling this sample as a mixture of two unobserved populations of crabs fit the data better than modeling the population as a single normal distribution (1894). Pearson and his collaborators interpreted their findings as illustrating the existence of two sub-species of crab (McLachlan & Peel, 2000). This historical example highlights the primary purpose for using mixture models in the behavioral sciences, which is the examination of potential unobserved sub-groups on the construct(s) being examined (McLachlan & Peel, 2000).

The assumption entailed in the use of mixture models is that a categorical latent structure summarizes the data in a more theoretically meaningful manner than a continuous latent structure (Lubke & Neale, 2006). For example, Reboussin, Song, Shrestha, Lohman, & Wolson (2006) modeled underage problem drinking and alcohol-related problems as three distinct latent groups of adolescents rather than as two continuous latent factors. Mixture models, therefore, represent a taxonomical approach that assumes that the different sub-groups represent non-arbitrary categories of individuals or systems (Meehl, 1992). A taxonomical approach views inter-individual differences on indicator variables as resulting from differential membership in unobserved subgroups *and* variability within that group (Meehl, 1992). Indicator variables in mixture models are analogous to the manifest variables that are predicted by latent factors in factor analysis and structural equation modeling (SEM), as each are observed sets of items used to illustrate latent constructs (i.e., categorical in mixture models and continuous in factor analysis/SEM) (Loken & Molenaar, 2007; Molenaar & von Eye, 1994).

Mixture models have been used in a variety of manners in prevention research. These models have been used in the examination of cross-sectional discrete (e.g., Chung & Martin, 2001; Coffman et al, 2007) and continuous data (e.g., Pastor, Barron, Miller, &

Davis, 2007; Ventura, Loken, & Birch, 2006), discrete (e.g., Chung, Park, & Lanza, 2005; Lanza & Collins, 2006; Jones, Nagin, & Roeder, 2001) and continuous (e.g., Greenbaum et al, 2005; Muthén & Muthén, 2000) longitudinal data, and complex evaluations of intervention programs (e.g., van Lier et al., 2004). While the questions answered and results achieved vary widely across studies, each of these applications, as well as the models used in the current dissertation, can be viewed as elaborations upon the classic latent class set of models (Lazarsfeld & Henry. 1968; Goodman, 1974; Lubke & Muthén, 2005; Lubke & Neale, 2006). Latent class models, and their derivatives, assume that the heterogeneous response patterns within a given sample on a set of indicator variables can be sufficiently represented by a finite number of mutually exclusive latent groups, to which participants are assigned probabilities of membership (Graham et al, 1991; Muthén & Muthén, 2000).

Latent class mixture model solutions are examined sequentially, beginning with a single class and adding additional classes based on relative model fit and substantive concerns (Lubke and Muthén, 2005; Nylund, Asparouhov, & Muthén, 2006). In the behavioral sciences, mixtures are most often performed using maximum likelihood estimation via the expectation-maximization (EM) algorithm (McLachlan & Peel, 2000). However, Bayesian estimation methods are available for the estimation of these models (McLachlan & Peel, 200). For the remainder of this dissertation, the estimation of mixture models will be discussed in terms of maximum likelihood estimation (for more information about Bayesian mixture methods, see Gelman, Carlin, Stern, & Rubin, 1995; Lavine & West, 1992; Loken, 2004).

Assessing the fit of latent class models in maximum likelihood is not as straightforward as assessing the fit of structural equation models. Despite the fact that mixture solutions with different numbers of components are nested within each other, traditional likelihood ratio tests of model fit cannot be used to compare competing models due to regularity conditions required not being met (Nylund, Asparouhov, & Muthén, 2007). Instead, a set of alternative indices of fit have been designed. Some of the most commonly used indices are categorized as information criteria (Akaike, 1987; Schwartz, 1978; Sclove, 1987). These indices utilize a variety of adjustments to the log-likelihood of the solution. The Akaike Information Criteria (AIC) penalizes models based on the number of parameters estimated (Akaike, 1987), while the Bayesian Information Criteria (BIC) penalizes models based on both parameters estimated and sample size (Schwartz, 1978). Another method for selecting the appropriate mixture model involves the use of an adjusted likelihood ratio test (Lo, Mendell, & Rubin, 2001). Due to the fact that the likelihood differences between models with k and k+1 components are not chi-square distributed, Lo, Mendell, and Rubin (LMR) (2001) employed an approximation of this distribution through which models can be tested. The LMR method compares the statistical improvement in fit of the model when adding an additional component to a k component mixture (Lo, Mendell, & Rubin, 2001). As mentioned above, substantive concerns are also often taken into account when deciding upon the most appropriate mixture model to interpret (Lubke & Muthén, 2005). Specifically, class size distributions, distinguishability of latent classes, and model interpretability are often important in model selection.

Latent classes are distinguished by both the proportion of the sample who are members and the within group, item-response probabilities to the indicator variables used (Magidson & Vermunt, 2002). For example, Reboussin and colleagues (2006) found that 43% (group probability) of adolescents who drank alcohol could be labeled "non-problem drinkers", as they had low probabilities of recent drinking, recent binge drinking, and alcohol-related problems (conditional probabilities). An additional 27% of adolescents were labeled "regular problem drinkers" (group probability), as they had relatively high probabilities of recent drinking, recent binge drinking, and alcohol-related problems (conditional probabilities). Following the determination and interpretation of the most appropriate latent class model, the resulting classes are often examined for potential differences on observed background characteristics using a logistic regression mechanism (Chung, Flaherty, & Schafer, 2006; Lanza, Collins, Lemmon, & Schafer, 2007). These covariates are not part of the latent structure, but are associated with and can influence the grouping observed. In addition, class differences on distal outcomes are also commonly examined by classifying individuals into groups and comparing across classes (Clogg, 1995; Pastor et al., 2007).

Person-Specific Analysis

It is often the case that the findings observed in a large sample are generalized to an individual member of the sample being studied (Lamiell, 2003). A basic example of this, from simple regression, would be the interpretation that a one unit increase in an individual's score on X is associated with so many units increase in an individual's score on Y. However, a more appropriate interpretation of this association is that, *in the population*, *on average*, a 1 unit increase in X is associated with so many units increase in

Y. While this distinction may appear trivial, it can be of great importance, as research has shown that it is rarely the case that group level interpretations hold at the individual level (Hamaker, Dolan, & Molenaar, 2005; Kinugasa, Cerin, & Hooper, 2004; Molenaar, 2004). This is known as non-ergodicity.

Imagine two research designs examining the association between the same two constructs. The first study samples many individuals at a given time and estimates the relationship by pooling across the responses from each participant. The second study analyzes a single individual who is sampled at many time points and estimates of the association by pooling across the responses given at each time. In order for the association being examined to be ergodic, among other assumptions, the inter-individual variation observed between participants in the first study must generalize to the intra-individual variation seen across time for the individual in the second study (Molenaar, 2004). If the between- and within-person estimates are not equivalent, the researchers must assume either (a) the association between the two processes is non-ergodic or (b) the individual being examined in the second study is not truly a member of the population being examined in the first study. In the vast majority of cases, the former of the two explanations is most tenable, suggesting heterogeneity, across individuals, in the way in which the two constructs are related.

A process can also be non-ergodic when the data collection method for the sample and individual are identical. A study by Hamaker, Nesselroade, and Molenaar (2007) examined 22 individuals over 90 time points on 30 items relating to personality. Results showed that the group-level factor structure was widely dissimilar to the factor structures achieved based on the person-specific data. This heterogeneity in process can result in improper interpretations regarding the constructs over time when projecting findings from the group to the level of the individual. These inter-individual differences in intra-individual variation are not sufficiently addressed unless a focus is specifically placed on the study of the individual.

A growing body of literature has begun incorporating person-specific analyses into applied behavioral research. Researchers have examined the extent to which alcohol use on a given day could be predicted by use on previous days using person-specific time series analysis (Rovine & Walls, 2006; Warren, Hawkins, & Sprott, 2003). Others have focused primarily on examining and predicting intra-individual variability in energy intake using intensively collected person-specific data (Tarasuk & Beaton, 1991). Still others have examined the person-specific factor structure of cardiovascular health (Friedman, 2003) and patient-clinician relationship processes (Russell, Jones, & Miller, 2007) using P-technique factor analysis. Yet another area of research where person-specific analyses have been used is in reaction time experiments (Visser, Raijmakers, & van der Maas, 2009). In this study, multivariate time series (both continuous and categorical) were modeled as consisting of a set of unobserved, latent states that individuals move into and out of across the length of the study. A similar model is examined in paper 2 of the current dissertation.

Generalizability and Interplay between Mixture Models and Person-Specific Analysis

Mixture models and person-specific analysis each acknowledge and seek to account for inter-individual differences that exist within a population. Mixture models accomplish this by separating the population into relatively homogeneous sub-groups based on the observed indicators. While within-group associations/processes might not be ergodic, it is possible that the generalizations made from the level of the group, or latent class, to the level of the individual will be more valid than generalizations made from the level of the population to the level of the individual. Person-specific analyses, on the other hand, result in valid generalizations to the individual being studied. In essence, performing person-specific analyses on *N* individuals is theoretically analogous to performing an *N* group mixture model. A common problem, however, with the implementation of person-specific analyses is that applied researchers are often interested in generalizing beyond the individual(s) being studied.

Dissertation Papers

Mixture models were central in two of the three manuscripts presented below. The first paper examined the potential estimation problems, misclassification, and associated biases that can arise from estimating too many classes from too few indicator variables. Latent class models known to have identification problems were simulated, and the results of interpreting the output of these models were discussed, as were situations where identification concerns were mitigated. The third paper examined heterogeneous patterns of indoor tanning over time using longitudinal latent class analysis among college females in a randomized controlled, prevention trial. This study first sought to illustrate the efficacy of the intervention over a 6 month period. It then focused on illustrating the different classes of tanning patterns that exist in the population and the extent to which the intervention has differential effects on participants based on class membership. The second paper used person-specific analysis to examine the impact of daily weather conditions on daily indoor tanning of college-age females over a 12 week period. First, group-level and person-specific patterns of tanning were estimated and compared using unconditional Markov models. Second, daily weather conditions were included as time-varying covariates to both the group- and individual-level models. Results were then discussed in terms of person-specific patterns of indoor tanning and the potential utility of person-specific analyses in the examination of influences on these patterns.

Paper 1 - Lack of information: Estimation and validity concerns in latent class analyses

Overview of Latent Class Analysis

Latent class analysis (LCA) is rapidly increasing in popularity in the behavioral and social sciences (for example: Abar & Loken, 2010; Caldwell, Bradley, & Coffman, 2009; Coffman, Patrick, Palen, Rhoades, & Ventura, 2007; Feldman, Masyn, & Conger, 2009; Gerber, Wittekind, Grote, & Staffelbach, 2009; Laska, Pasch, Lust, Story, & Ehlinger, 2009; Nylund, Bellmore, Nishina, & Graham, 2007). Latent class models are primarily used to model unobserved population heterogeneity by dividing a sample into sub-groups based on responses to a set of indicators (Van Leeuwen, Mervielde, Braet, & Bosmans, 2004). LCA assumes that heterogeneous patterns of responses to a set of discrete indicators are due to an unobserved, categorical latent structure that can be represented by *k* mutually exclusive latent classes (Goodman, 1974; Lazarsfeld & Henry, 1968; Muthén & Muthén, 2000). LCA assumes conditional independence within class, such that any population level associations between indicators are fully accounted for by latent class membership.

Two types of parameters are estimated in LCA. The first type is the group probabilities, which describe the relative sizes of the latent classes. Some researchers have used the term γ (gamma) parameters to represent these group probabilities (Lanza, Collins, Lemmon, & Schafer, 2007). The second type of parameter is the conditional item-response probabilities, which represent the probability, given class membership, of responding in a certain manner to the manifest variables included in the model (Magidson & Vermunt, 2004). These conditional probabilities have also been termed ρ (rho) parameters (Lanza et al., 2007). The model underlying LCA is that, using these two types of parameters, any particular pattern of responses to discrete indicators can be represented by the following formula:

$$P\ (X = x) = \sum_{k=1}^{K} P\ (k) P\ (X = x \mid k) \tag{1}$$

with *P* (*k*) representing the marginal group probability and *P* (X = *x* | *k*) representing the probability of response pattern X = x within latent class *k*. A similar model when applied to continuous data is known as continuous LCA, normal mixture models, or latent profile analysis (LPA) (Molenaar & von Eye, 1994). The posterior probability of belonging to class *k* given observed data (X = x) is:

$$P\ (k \mid X = x) = \frac{P(X = x \mid k)\ P\ (k)}{\sum_{k=1}^{K} P\ (X = x \mid k)\ P\ (k)} \tag{2}$$

with *k* representing the group probability and $P(X = x \mid k)$ representing the probability of response pattern X = *x* in class *k*.

In order for latent class models to be uniquely identifiable at the maximum likelihood estimate, they must satisfy two conditions (Dayton, 1998). First, the Jacobian matrix of the model parameters must be positive definite, implying a lack of collinearity among the estimated parameters (i.e., non-full rank Jacobian matrix; see Goodman, 1974 for details). The second condition is that the model must have positive degrees of freedom (df). Degrees of freedom in LCA with binary indicators are 2^v- *P* - 1, with *v* as the number of indicator variables and *P* as the total number of parameters estimated. For example, consider a situation where 4 binary indicators are used to estimate 2 latent classes. Nine parameters are estimated in this model (i.e., 4 conditional probabilities per class and 1 group probability), making the df = 2^4 – 9 – 1 = 16 – 10 = 6. A more generalized formula for polytomous indicators would be $R - P - 1$, with R representing the total number of potential response vectors (e.g., 0, 0, 0, 0).

It is possible for a latent class model to have positive df with a non-positive definite Jacobian matrix. For example, Goodman (1974) demonstrated that the 4 indicator - 3 class model, despite having 1 df, was not identified. Specifically, the Jacobian matrix (15 non-redundant response patterns X 14 estimated model parameters) was shown to lack full rank (rank = 13). Non-identified models can be made estimable by imposing a priori constraints (e.g., fixing parameters, imposing equality constraints) that limit the number of parameters being estimated (Goodman, 1974). When these a priori constraints are not set, many statistical programs will make assumptions without input from the user in order to provide interpretable solutions and output (Dayton, 1998). This might, as first glance, appear desirable in that it results in an identified solution. However, if the constraints made are not in line with the true population model (i.e., inappropriate group and/or conditional probabilities), a variety of undesirable results are likely to occur. The current paper will examine situations where these unidentified models are estimated, the resulting effects on misclassification of cases and distal outcomes, and ways to mitigate these effects.

External Variables in Latent Class Analysis

A common applied practice in the use of LCA is to relate the latent classes to variables not included in the model as indicators. The most common and accepted method for accomplishing this goal is through the inclusion of covariates to the class solution in the model (Dayton & Macready, 1988; Lanza et al., 2007). These models have been described as conditional latent class analyses (Feldman, Maysn, & Conger,

2009) or concomitant latent class analyses (Dayton & Macready, 1988). These manifest covariates are most often demographic characteristics or constructs theoretically associated with the categorical latent structure being modeled. Latent class membership is regressed onto these covariates using multinomial logistic regression (Lanza et al., 2007; Muthén & Muthén, 1998-2007), with the associated coefficients termed β (beta) parameters. For example, Coffman and colleagues (2007) modeled 4 latent sub-groups of 12th grade students with differential motivations for drinking alcohol and used self-reports of alcohol use (e.g., frequency of drunkenness) as covariates predicting class membership.

A second way that external variables are analyzed in latent class analysis involves classification into most likely class and analyzing the resulting groups on the external, dependent variables (Pastor, Barron, Miller, & Davis, 2007; Roeder, Lynch, & Nagin, 1999). Individuals are assigned to classes based on their highest posterior probabilities, and traditional regression/ANOVA methods are then used to compare groups. For example, Breslau, Reboussin, Anthony, & Storr (2005) examined 3 distinct classes of posttraumatic stress disorder (PTSD) which were found to be predictive of self-reports of medical care and life disturbances due to PTSD. This practice has received some criticism, as some researchers have discussed the potential pitfalls that arise from what has been termed a “classify-analyze” approach (Clark & Muthén, under review; Clogg, 1995; Hagenaars, 1993; Roeder, Lynch, & Nagin, 1999).

Clogg (1995) and others (Roeder et al., 1999) pointed out that classifying individuals into most likely class and analyzing as if membership were known (“classify-analyze”) ignores the inherent uncertainty in probabilistic assignment. Loken (2004) pointed out that this approach also ignores the uncertainty in the parameter estimates of the model. Ignoring these uncertainties can result in biased class comparisons and biased standard errors when individuals are misclassified (Clark & Muthén, under review: Hagenaars, 1993; Roeder et al., 1999). For example, under the "classify-analyze" approach, individuals with posterior probabilities of 1.0 and .51 in class *k* will be treated as equal members of the class. In order to circumvent the issue of treating class membership as known, researchers have proposed including the distal outcome(s) as exogenous variables in the estimation of the model (Clark & Muthén, under review). While this approach does not assign membership, it does allow the distal outcome to have an impact on the substantive meaning of the classes (i.e., impact group and conditional probabilities; Clark & Muthén, under review), which is often not desirable. For example, researchers examining the association between infant temperament on childhood behavioral inhibition (Loken, 2004) might not want outcomes collected at 4 years-of-age to influence class membership defined at 4 months-of-age. A relatively new approach that has been put forward has been labeled pseudo-class draws (Asparouhov & Muthén, 2007; Loken, 2004; Wang, Brown, & Bandeen-Roche, 2005). In this approach, class membership is determined by a set of random draws made using each participant's posterior probabilities. The current study will examine the potential benefits of using covariates in models with identification concerns, as well as the potential problems with using the "classify-analyze" approach in these types of models.

Classification in Latent Class Analysis

In order to understand the degree to which classifications made in LCA are accurate, researchers must be confident in the appropriateness of the model being fit. A set of fit indices (for example: Akaike, 1987; Lo, Mendell, & Rubin, 2001; Schwartz, 1978) have been developed to provide empirical support for the number of latent classes chosen. These measures are crucial to latent class modeling, as the number of latent classes present is most often unknown prior to analysis (Nylund, Asparouhov, & Muthén, 2006). An additional measure of distinction between classes, entropy (Celeux & Soromenho, 1996), has also been designed to assist in the selection of models by providing evidence of the degree of class overlap. An entropy value of .80 indicates acceptable classification of individuals to latent classes (Lubke & Muthén, 2005). Posterior probabilities of group membership are closely tied to entropy, such that high entropy values indicate high average posterior probability of group membership within groups.

The misclassification rate in LCA is defined, in the current study, as the percent of the time that an individual's "true" latent class is not the class for which he/she has the highest posterior probability. The misclassification rate for each case is assumed to be 1 – highest posterior probability, such that the misclassification rate would be 20% for an average posterior probability of .80 (van der Heijden, Dessens, & Bockenholt, 1996). However, these nominal misclassification rates are only relative to the estimated model; if the parameter estimates do not reflect the population model, then clearly distinguished classes with high posterior probabilities of class membership will not necessarily lead to good "true" classification. It is also possible that a model can do an acceptable job of modeling latent classes in the sample but do a relatively poor job of classifying individuals. For example, the "true" number of classes can be modeled and the general pattern of conditional probabilities (e.g., relative high/low probabilities) can approximate the "true" parameter values, but high rates of misclassification remain possible in a handful of situations, particularly when boundary solutions are observed.

It is often the case in LCA models with distinct indicator variables (i.e., indicators that are strongly related to latent class structure) that the within class conditional probability for one or more indicators sit on the boundary solution of 0 or 1 (Clogg, 1995). These values are said to be boundary solutions as they represent the lower and upper bounds of possible parameter values. When conditional probabilities sit on boundaries, the variables are no longer probabilistic indicators, as they now function, in a sense, as screening instruments for membership in the class. It follows then that the classes being estimated are no longer purely latent. For example, Lanza et al. (2007) illustrated a class of "non-drinkers" with conditional probabilities of 0 across seven indicators of alcohol use and a class of "heavy drinkers" with conditional probabilities of 1.00 on five indicators. One consequence of these types of solutions is that even in situations where an individual's "true" membership is class *k* (e.g., non-drinker) and the majority of his/her responses indicate likely membership in class *k*, if he/she has an atypical response to an indicator on a boundary solution (e.g., 0, 0, 0, 0, 0, 0, 1), the posterior probability of membership in class *k* will be .00 and the individual will be misclassified.

In the many analyses, these boundary solutions may correctly represent the population parameters. However, as mentioned above, when the models being estimated are not identified at the maximum likelihood estimate (e.g., 4 binary indicators – 3 latent classes), parameters are often fixed in the estimation procedure without user input to make the models estimable and interpretable (Dayton, 1998; Goodman, 1974). This can result in conditional probabilities being set to 0 or 1.00 when the "true" class structure does not imply these extreme values. Any misclassification errors, including those resulting from these boundary estimates, will result in biased conditional mean estimates on the distal outcomes analyzed using the "classify-analyze" approach or any method utilizing the estimated posterior probabilities (e.g., pseudo-class draws). This is a topic that has received limited investigation despite its potential implications for applied research.

The purpose of the current study is to examine the extent to which latent class analysis software is able to identify known groups in an under-identified model that *appears* acceptable due to positive degrees of freedom. The estimation characteristics, misclassification rates, and bias in distal outcomes were examined. In addition, a series of methods for mitigating these concerns were examined.

Basic Model

A three class model with four indicators was used as the primary template for the analyses. As mentioned above, this model is known to have identification concerns. Despite this fact, models estimating 3 classes from 4 indicators are relatively common in the behavioral and social sciences (for example, Loken, 2004; Pastor et al., 2007). The total number of cases in each simulated dataset was 1000, representing a relatively large yet reasonable sample size for most substantive researchers using LCA. Classes were simulated to be of approximately equal size (i.e., 33%, 33%, and 34%). Indicator variables were binary (e.g., yes/no), with the first class having a high probability of endorsing all items, the second class having a low probability of endorsing all items, and the third class having a high probability of endorsing half of the items and a low probability of endorsing the other half (see Table 1 for the population model). A continuous distal outcome/dependent variable was also simulated, with the first class having a mean of 0, the second having a mean of 1.0, and the third having a mean of .5 (SD's were all .2). In addition, a continuous covariate was simulated with varying degrees of association with unobserved latent class indicator variable.

The first set of models was simulated with 4 latent class indicators with high probabilities of endorsement set to .90 and low probabilities set to .10. These conditional probabilities would be considered highly desirable to behavioral researchers using latent class analysis as they are indicative are clear class separation. Supplementary simulations were also performed with more distinct (i.e., conditional probabilities = .99/.01) and less distinct (i.e., conditional probabilities = .80/.20) latent class indicators. For each set of simulations, results were averaged across 100 independent replications.

Unconditional Model – 4 Indicators

Using popular latent class software (Muthén & Muthén, 1996-2007), the 3 class model always fit the data best according to the Bayesian Information Criteria (BIC; Schwartz, 1978) and the Lo-Mendell-Rubin adjusted likelihood ratio test (aLRT; Lo, Mendell, & Rubin. 2001). Twenty percent of the datasets resulted in a solution with a non-positive definite Jacobian matrix, such that a warning message alerted researchers that the standard errors of the model parameters were not reliable and that caution should be taken when interpreting the solution. Of the remaining 80% of solutions, 67 of 80 datasets had 3 or 4 parameters at the boundary (see Table 2). These conditional probabilities have standard errors set to zero, and the indicators essentially function as manifest variables. Since these probabilities and their associated standard errors are fixed, the number of parameters requiring estimation is reduced and the models *appear* to be identified and uniquely estimable.

Cross-tabulations between true class and most likely class based on posterior probabilities showed that, on average, approximately 14% of cases were misclassified (range = 10-16%). Figure 1 provides a graphical depiction of where these misclassifications tend to occur using a single representative data set. Within each "true" class, the distribution of posterior probabilities of membership in that class (e.g., true class 1, posterior probability of membership in class 1) is not smooth. For a portion of the sample, the posterior probabilities of membership in their true class are zero due to conditional probabilities lying on the boundary of the parameter space. Referring to formula 2 above, it becomes clear that any cases with response vector that contains an atypical response to an item lying on a boundary in a given class will have a posterior probability of zero for that class (i.e., the numerator of the equation is zero). If a researcher were unaware of these model estimation problems, this percentage misclassified would be somewhat surprising given that indicator variables with values as consistently disparate as .90 and .10 are signs of clear class distinction. Moreover, this misclassification occurs despite the fact that the average posterior probabilities within the most likely class were greater than .90 for each latent class, further indicating clearly defined classes.

This misclassification resulted in substantially biased estimates of class means on the distal outcome. Using the "classify-analyze" approach, the average difference in absolute values between "true" and observed was .06 for class 1 (~1/3 S.D), .04 for class 2 (~1/5 S.D.), and .06 for class 3 (~1/3 S.D.) (see Figure 2). In general, the mean of class 1 was overestimated and the mean of class 3 was underestimated. As mentioned above, the presence of boundary solutions not in line with the population model results in inaccurate posterior probabilities. Given that the classifications made under the “classify-analyze” approach are dependent upon appropriate representation of the population model, these biased estimates on the distal outcome were expected. Further, these biases remained relatively constant even when employing pseudo-class draw methods mentioned above (i.e., randomly draw class membership using posterior probabilities) and averaging across 5 imputed datasets. This finding was also not surprising, given that the pseudo-class draws are based on the estimated posterior probabilities of class membership. In these situations, where the population model is not well represented, the use of pseudo-class draws will not correct the underlying problem leading to the bias seen in the “classify-analyze” approach.

As mentioned earlier, with “true” conditional probabilities that do not sit on a boundary (i.e., $0 < p < 1$), it is possible that individuals whose true class had a specific pattern of responses (e.g., endorse all items) may endorse an atypical pattern (e.g., endorse all items save 1). There are multiple ways that these atypical response patterns may arise, with the most likely being within group variance. Within a given true latent class, it would be unreasonable to expect to see perfect homogeneity given imperfect class indicators. Some individuals, therefore, will deviate from the modal response pattern as a result of variance. To better highlight this issue of within class variability, simulations were run with the only changes from the basic model being the use of less distinct indicator variables (i.e., .80/.20 rather than .90/.10). It is likely that these probabilities are more representative of common indicators of latent classes in the behavioral and social sciences. In these simulations, 53% of solutions were shown to have non-positive definite Jacobian matrices, and in the 47% "identified" solutions, 40 solutions had 2 or 3 boundary solutions (Mode = 2) despite the "true" parameter values lying even further from the boundaries than the previous simulations performed. The average misclassification rate in this set of simulations increased to 28%, with worse distal recovery bias than the situations with more distinct indicators (~3/4 S.D. bias for classes 1 and 2; ~1/5 S.D. bias for class 3). The classification and parameter recovery in unidentified models become worse the further the "true" conditional probabilities move from the boundary solutions. This finding was further supported by simulations performed with conditional probabilities approaching the boundaries (i.e., .99/.01), where classification was found to be nearly perfect due to boundary estimates representing the population model well.

To reiterate, the model that has been simulated to this point suffers from estimation problems. These identification concerns, coupled with the eventuality of atypical response patterns within true class, have been shown to result in high misclassification rates and poor parameter recovery when the population model does not imply boundary solutions. These findings emphasize the need to understand ways in which the problems associated with the interpretation of these models can be limited through the introduction of additional information.

Unconditional Model – 6 Indicators

The first way in which additional information was added to the model was through increasing the number of indicators used from 4 to 6. There are several prospective reasons why increasing the number of equally distinctive indicators might improve estimation and classification. The first and most obvious reason is that 3 classes estimated with 6 indicators is identified. Since the model is identified a priori, no parameters require artificial fixing at boundaries. Another reason additional indicators are expected to improve classification involves the above discussed potential for atypical response patterns within true class. In the 4 indicator – 3 class simulations above, a single atypical response on the 3rd or 4th indicators for an individual in class 1 (e.g., observed pattern of 1,1,1,0 as opposed to ideal pattern of 1,1,1,1) or on the 1st or 2nd indicator for an individual in class 2 (e.g., 0,1,0,0 as opposed to 0,0,0,0) results in a case appearing as similar to their true class as individuals in class 3 (i.e., ideal pattern of 1,1,0,0). With 6 indicators, the presence of a single atypical response (e.g., 1,1,1,1,1,0 for an individual in class 1) leaves the an individual's response pattern appearing more similar to his/her true class than to either of the other 2 classes. As such, more accurate parameter estimation was expected, as was decreased misclassification and distal recovery bias. Finally, on a substantive note, the inclusion of additional indicators may theoretically improve construct representation. The categorical latent construct being defined may be too complex to capture using a small number of imperfect indicators.

The same 3 class model used above was simulated, with the exception of the 2 additional indicators variables added. The 3 class solution provided the best statistical fit for all simulated data sets, no boundary estimates were observed, and each solution had a positive-definite Jacobian matrix. The associated misclassification rate averaged 4% (Range = 3 – 6%) and substantial improvements were seen in predicting the distal outcomes, such that the recovered means averaged .02, .98, and .50, respectively. These decreases in misclassification and improvements in distal recovery are directly associated with improvements in the within-class distributions of the posterior probabilities. Figure 3 illustrates an example of these distributions which includes much fewer problematic cases than observed when using 4 indicators (see Figure 1). In addition, the true model parameters were better recovered in the 6 indicator setting (e.g., $M_{\text{group probabilities}}$ =.33, .32, and .35) than in the 4 indicator setting.

Conditional Model – 4 Indicators and 1 Covariate

The second way that additional information was added to the model was through the inclusion of a covariate. Modeling a continuous covariate predicting latent class membership alters the model (Nylund et al., 2007), as well as the associated Jacobian matrix. The addition of a clearly delineated covariate, with mean differences across classes, might improve classification and parameter estimation. To examine this question, the basic 4 indicator – 3 class model was again used and expanded to include the simulated continuous covariate. Four covariates of varying magnitude of effects were simulated and examined sequentially – near-perfect, strong, weak, and non-formative.

For the first set of conditional LCA simulations, using the near-perfect covariate, the “true” covariate means were separated by 2.5 and 5.0 standard deviations (M_1 = .00, M_2 =1.00, M_3 = .50; SDs = .20; see Table 1). The inclusion of this covariate to the model eliminated issues of non-positive definite Jacobian matrices and boundary solutions, as neither was observed across 100 simulated datasets (see Table 2). In addition, the standard errors of the model parameters were also greatly decreased, on average, when compared to the standard errors of parameters in the unconditional model. The average misclassification rate associated with this model was, again, 4% (Range = 2 – 5%). Similar to the 6 indicator model, the true model parameters were recovered better with the inclusion of a near-perfect covariate (e.g., $M_{\text{group probabilities}}$ = .32, .33, and .35) than in the unconditional, 4 indicator model.

While these results are encouraging, one must consider the feasibility of the covariate being modeled and the effects being seen. In the above simulations, group means were separated by 2.5 and 5 standard deviations. It is likely that these non-overlapping within class distributions on the covariate are strongly pulling apart the true latent class membership (i.e., covariate impacting group probabilities), which, in turn, is resulting in better conditional probability recovery. If appropriate group probability estimates are being determined largely by this near-perfect covariate, appropriate conditional probabilities may be induced. In practice, it would also be quite rare to observe such clear distinctions on an external variable based on latent class membership.

The second set of conditional LCA simulations used, what we are terming, a "strong" covariate. In these simulations, the "true" means were separated by 1 and 2 standard deviations (.M_1 = .00, M_2 =.40, M_3 = .20; SDs = .20; see Table 1). The inclusion of this strong covariate, again, eliminated all non-positive definite solutions, and a boundary solution was only observed 6% of the time. Moreover, the average misclassification rate for these models was 10% (range = 7 – 12%), representing an improvement over the basic model without covariates. Covariate effects of this "strong" magnitude are more reasonable to observe than those associated with the "near-perfect" covariate, and it also appears that these effects resulted in much improved parameter recovery than the unconditional, 4 indicator model.

The third set of conditional LCA simulations used a "weak" covariate, with the "true" means separated by only 1/4 and 1/2 standard deviations (.M_1 = .00, M_2 =.10, M_3 =

.05; SDs = .20; see Table 1). The inclusion of this weak covariate also eliminated all non-positive definite solutions, but boundary solutions were observed in 96% of datasets simulated, with 74 of the 96 solutions exhibiting 2 or 3 boundaries (see Table 2). The average misclassification rate associated with these models was 13% (range = 10 – 17%), which represents a very marginal improvement over the unconditional, 4 indicator model.

The fourth and final set of conditional LCA simulations employed a completely non-informative covariate in terms of distinguishing between classes (i.e., *Ms* = .00; see Table 1). Results of this set of simulations revealed that relatively few datasets resulted in non-positive definite solutions (3%), but each of the remaining datasets demonstrated boundary solutions, with 74 solutions exhibiting 2 or 3 boundaries (Mode = 2). Relatedly, the remaining, non-boundary parameters were relatively poorly recovered (e.g., $M_{\text{group probabilities}}$ = .28, .33, and .38). The average misclassification rate for these models was 14% (range = 11 – 17%). In general, models incorporating a completely non-informative covariate appear to result in identical misclassification and parameter recovery problems as the unconditional, 4 indicator – 3 class models, with the exception of the non-informative covariate models being much less likely to exhibit a non-positive definite Jacobian matrix. It may be that the inclusion of the additional continuous variable in the model, regardless of its empirical value, results in a full-rank Jacobian matrix and an estimable solution.

Overall, the results of these 4 sets of simulations imply that the improvement in the accuracy and validity of the conditional latent class model over the unconditional model is contingent on the magnitude of the covariate differences seen across classes. However, the estimation and parameter recovery observed were each improved with the inclusion of any covariate that differs across latent classes (i.e., near-perfect, strong, and mild).

Summary of Changes Made to the Basic Model

The above simulations examined the potential problems associated with examining and interpreting latent class models in a situation that is known to be not identified (Dayton, 1998; Goodman, 1974) and in which the user rarely receives an alert to this lack of identification. We demonstrated that relatively poor parameter estimation, high rate of misclassification, and poor predictive power were observed in the 4 indicator – 3 class model. As described by Goodman (1974), there is not enough information in 4 binary indicators to estimate 12 conditional probabilities and 2 group probabilities. To be more specific, this model has 1 unidentified parameter. Therefore, in order for these models to be estimable, a single parameter restriction must be made. This is accomplished by LCA software (primarily without the knowledge of the user) in models where at least one conditional probability falls on a boundary (0 or 1). The current study showed that these models happen quite often even in situations where the population, or “true”, model does not call for these extreme values.

The current study illustrated that much of the problems with interpreting the results of the basic, 4 indicator – 3 class model were eliminated by the use of additional indicators to make the model identified or by the inclusion of an informative covariate that significantly predicts latent class membership. Each of these model changes suffers from some degree of concern over logistical practicality. For example, it could prove difficult to find 2 additional indicators of the same categorical latent structure that are as equally distinct (i.e., .90/.10) as the 4 indicators originally modeled. Despite logistical concerns, both of these methods illustrate a way to enhance the accuracy and validity of these models.

Yet another way to eliminate the problems associated with non-identified latent class models that has not been discussed to this point is the use of a priori parameter restrictions to create identified models (Goodman, 1974; Magidson & Vermunt, 2001). Staying with the basic model discussed throughout the paper (4 indicator – 3 class), imposing a single constraint will identify the model. In the population discussed above (see Table 1), this constraint might be placed on either the group or conditional probabilities. For example, researchers can set the group probabilities of classes 1 and 2 equal, or two conditional probabilities *within* class 1 or class 2 can be constrained to be equal. These types of restrictions are in line with the population model and will eliminate identifiability concerns. However, the major problem with this method lies in the *unobserved* nature of the classes being estimated. The vast majority of the time, when researchers are using latent class analysis, the analyses are exploratory as the true population model is unknown. In most cases, the number of classes that sufficiently describe the data are unknown (Nylund et al., 2006), much less the proportions with which these classes exist and the conditional response probabilities within these classes. Imposing the “wrong” parameter constraints will likely result in the same problems (e.g., misclassification, poor parameter recovery) seen in non-identified models.

Beyond the Basic Model and Suggestions for Practice

To this point, the current study has focused exclusively on a basic example that is known to have estimation concerns. What must be stressed is that concerns regarding sufficient information in latent class indicators for model estimation are not limited to this situation. It is often the case that researchers estimate and interpret a relatively large number of classes from a relatively small number of indicators. Illustrative simulations were performed to demonstrate this point. While the 5 binary indicator – 5 class model has 7 df, each data set simulated converged at a solution with multiple (i.e., 5 +) boundary solutions, despite true probabilities being simulated at .9/.1, .8/.2, and .7/.3 across separate data sets. While researchers have found this model to be uniquely estimable (Magidson & Vermunt, 2001), this is likely only the case when the population model dictates the need for boundary solutions (i.e., 1 class with a uniform response patterns of 0, 0, 0, 0, 0). The findings from the current simulations are supported by other researchers who have shown that the unconditional 5 indicator – 5 class solution is not identified (Formann, 2003). These simulations begin to show the potential extent of the issue of identifiability in latent class models. Calculating the Jacobian matrix for all possible combinations of *x* indicators and *k* latent classes would be analytically complex and computational intensive (Dayton, 1998; Magidson & Vermunt, 2001). A preliminary step that may be sufficient for mitigating these calculations might be found in the factor analytic literature (Loken & Molenaar, 2007; Molenaar & von Eye, 1994).

Model identification issues like those discussed in the current study are commonly brought up in the context of factor analysis and structural equation modeling (Bollen, 1989; Tabachnick & Fiddell, 2001). These concerns are relevant to the current study, as researchers have demonstrated a formal correspondence between factor analysis and continuous latent class analysis (LPA) (Loken & Molenaar, 2007; Molenaar & von Eye, 1994). A *k* factor exploratory factor analysis is statistically equivalent, up to the second order moments, to a *k* + 1 profile solution. Given this correspondence, estimating

3 classes using 4 indicators is analogous to estimating 2 factors from 4 indicators. In factor analysis, identification of 2 latent factors using only 2 indicators each is only possible under specific, restricted circumstances (Tabachnick & Fidell, 2001). In contrast, the 6 indicator – 3 class model is equivalent to a 2 factor model with 3 indicators each, which requires no restrictions for estimation. Researchers seeking to use latent class analysis might capitalize on this relationship between models by using model identification rules from factor analysis as guidelines for the number of classes that can be effectively estimated in latent class analysis. For example, while the 5 indicator – 5 class model has been proposed in LCA without constraints, a 4 factor solution with 5 indicators would be unacceptable without multiple a priori parameter constraints being imposed. It is probable that the strict use of factor analytic indicator guidelines in LCA is a conservative approach, but the validity and predictive power of the solutions achieved will be likely be strengthened.

Conclusions and Future Directions

The current study demonstrates the potential consequences of fitting and interpreting latent class models that are not identified. In situations where a large number of classes are fit relative to the number of indicators used, the validity of model parameters are often compromised (i.e., estimates are artifacts of the estimation problems) and can result in inappropriate inferences about population subgroups. The current study also showed several ways that these types of models can be modified to improve interpretation, as well as providing suggestions for how to avoid these types of situations entirely. To complement these contributions, there are several directions for future research that must be explored for a complete understanding of the issue of information in latent class models. The current study only examined latent class models using discrete indicators. Additional research should be done examining the effects of indicator distinction (e.g., 1 S.D. separation between profiles vs .2 S.D.) and indicator quantity on misclassification in latent profile models. We would expect to see better classification in profile models when using a greater quantity of indicators relative to the number of classes estimated given that identifiability concerns can be even more pronounced in profile models due to the need to estimate conditional means and variances. Perhaps more importantly, future research may seek to demonstrate the identifiability conditions of each foreseeable combination of indicator and class number. This is a complicated and computationally intensive process that could enhance the appropriate use of latent class models in the behavioral sciences by providing even more explicit guidelines for acceptable modeling practices.

Despite these unexplored avenues, the current manuscript provides practical knowledge to substantive researchers interested in latent class models. The availability of powerful software for this type of modeling (Muthén & Muthén, 1998-2008; Lanza et al., 2007; Vermunt & Magidson, 2005) makes it imperative that users have accessible guidelines for the implementation and interpretation of these models.

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Table 1

Basic Population Model Used in the Simulations

	Class 1 “All High Class” 33%	Class 2 “All Low Class” 33%	Class 3 “High/Low Class” 34%
Conditional Probabilities			
P (X_1 = Yes | Class)	.90	.10	.90
P (X_2 = Yes | Class)	.90	.10	.90
P (X_3 = Yes | Class)	.90	.10	.10
P (X_4 = Yes | Class)	.90	.10	.10
Distal Outcome - Mean	.00	1.00	.50
(SD)	(.20)	(.20)	(.20)
Covariates – Mean (SD)			
Near-Perfect	.00	1.00	.50
	(.20)	(.20)	(.20)
Strong	.00	.40	.20
	(.20)	(.20)	(.20)
Weak	.00	.10	.05
	(.20)	(.20)	(.20)
Non-informative	.00	.00	.00
	(.20)	(.20)	(.20)

Table 2

Simulation Results for the 3 Class Model

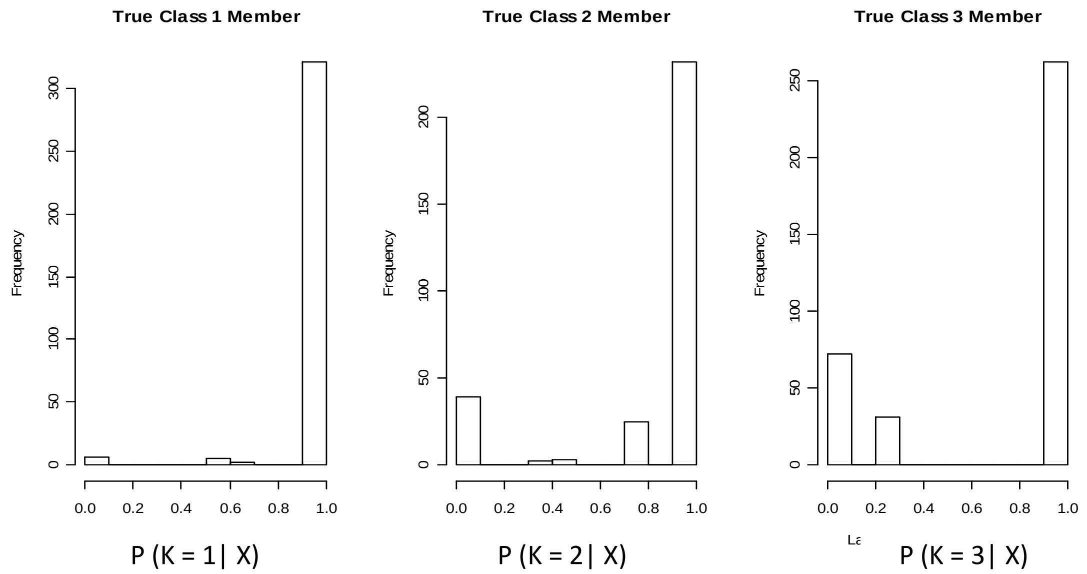
	Average Misclassification Rate	Frequency of Boundary Solutions [a]				
		0	1	2	3	4+
4 Indicators						
Unconditional Model	14%	0	5	33	34	8
Conditional Model - Near-Perfect Covariate	4%	100	0	0	0	0
Conditional Model - Strong Covariate	10%	94	6	0	0	0
Conditional Model - Weak Covariate	13%	4	34	40	20	2
Conditional Model - Non-informative Covariate	14%	1	20	38	36	2
6 Indicators						
Unconditional Model	4%	100	0	0	0	0

[a] This represents the frequency of boundary solutions observed when a positive-definite information matrix was observed.

Note: For the results discussed in this table, true conditional probabilities were .90/.10.

Figure 1

Distribution of posterior probabilities of class membership given true class membership with 4 indicators in an example dataset



True Conditional Probabilities	True Conditional Probabilities	True Conditional Probabilities
.90, .90, .90, .90	.10, .10, .10, .10	.90, .90, .10, .10

Estimated Conditional Probabilities	Estimated Conditional Probabilities	Estimated Conditional Probabilities
.91, .91, 1.00, .83	.16, .17, .09, .11	.91, .91, .00, .17

Figure 2

Distribution of distal outcome biases in the 4 indicator – 3 class model

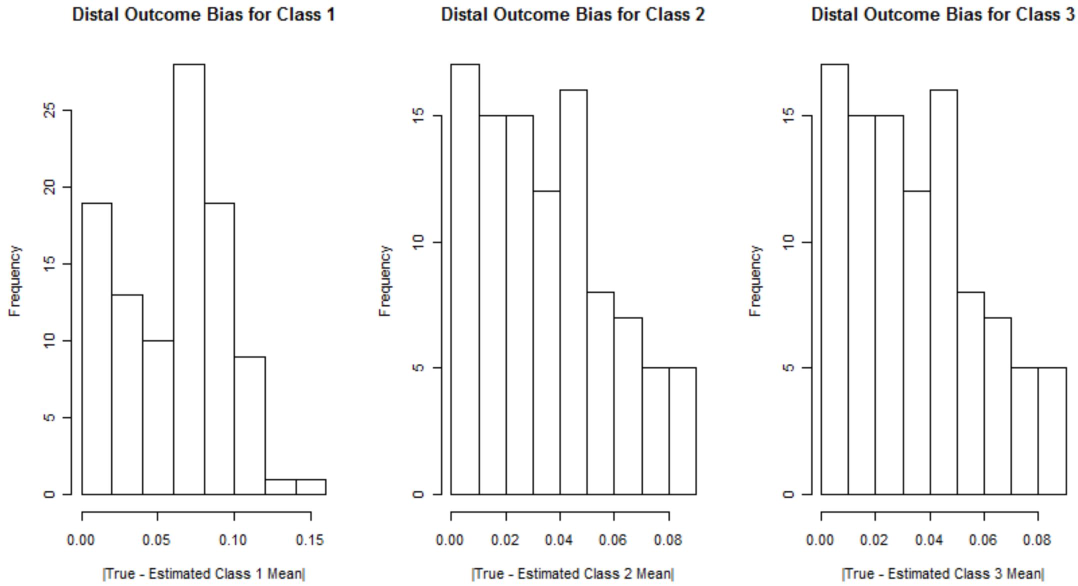
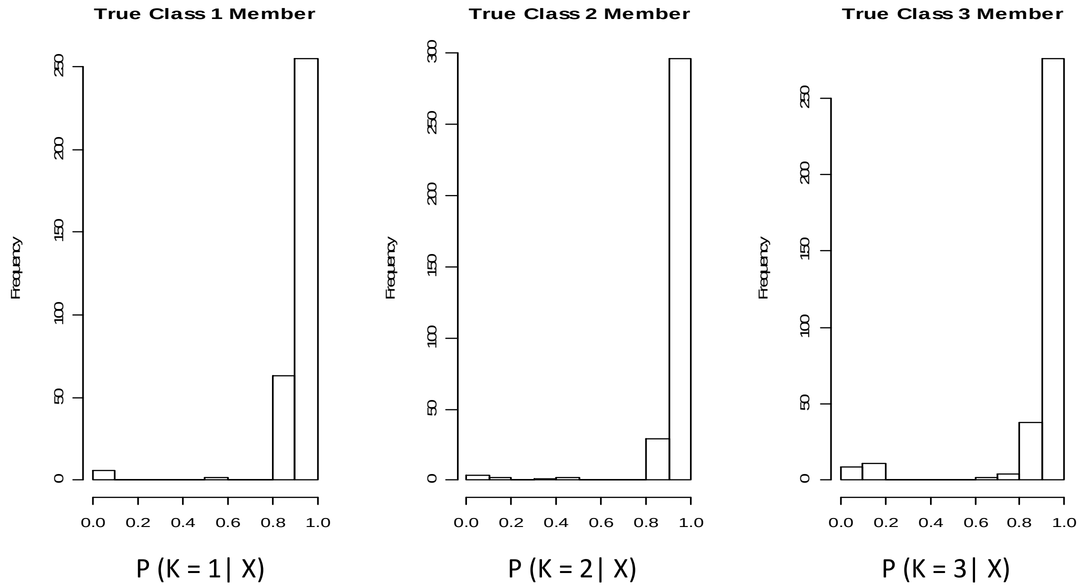


Figure 3

Distribution of posterior probabilities of class membership given true class membership with 6 indicators in an example dataset



True Conditional Probabilities	True Conditional Probabilities	True Conditional Probabilities
.90, .90, .90, .90, .90, .90	.10, .10, .10, .10, .10, .10	.90, .90, .90, .10, .10, .10

Estimated Conditional Probabilities	Estimated Conditional Probabilities	Estimated Conditional Probabilities
.92, .92, .90, .91, .89, .90	.10, .06, .08, .09, .12, .10	.84, .88, .89, .12, .14, .12

Paper 2: The influence of weather on person-specific tanning behaviors

Over one million new diagnoses of skin cancer are made in the United States every year (National Cancer Institute, 2007). More than 11,000 Americans die annually as the result of skin cancer (American Cancer Society, 2008), and the annual economic impact associated with skin cancer treatment in the U.S. exceeds $1 billion (Bickers et al., 2006; Chen et al., 2001). One source of hope, however, is that skin cancer is highly preventable in humans (Glanz & Mayer, 2005).

Both laboratory and epidemiological research have shown ultraviolet radiation (UVR) to be the leading cause of skin cancer (Almahroos & Kurban, 2004; Bennett, 2008; Hussein, 2005; Moan, Dahlback, & Setlow, 1999; Quinn, 1997), accounting for approximately 80% of all diagnoses (Armstrong & Kricker, 1993). The U.S. Department of Health and Human Services declared UVR from the sun and artificial sources, such as tanning beds and lamps, a known carcinogen (2000). Avoiding unnecessary UVR exposure and using sunscreen with a relatively high skin protection factor (SPF) (e.g., greater than 15) has been shown to be effective at reducing the likelihood of skin cancer diagnoses and skin damage, in general (Gilchrest, 2007; Stern, Weinstock, & Baker, 1986; Thompson, Jolley, & Marks, 1993).

While the public is generally well informed about the health risks associated with UVR exposure (Knight, Kirincich, Farmer, & Hood, 2002; Robinson, Kim, Rosenbaum, & Ortiz, 2008), this knowledge alone does not appear to be impacting tanning behaviors, as intentional UVR exposure continues to increase (International Tanning Association, 2003, 2007). There has been a tremendous growth in the indoor tanning business, with the number of U.S. indoor tanners doubling to roughly 30 million over the past decade

(ITA, 2007). Research has shown the primary motivation for this tanning and associated UVR exposure to be appearance enhancement (Cafri et al., 2008; Hillhouse, Stair, & Adler, 1996; Hillhouse, Turrisi, & Kastner, 2000; Jackson & Aiken, 2000; Miller et al., 1990). These motivations are largely fostered and reinforced by the popular media, where the majority of images show models and celebrities with moderate to dark tans using few sun/UVR protective behaviors (e.g., wearing hats or protective clothing; Dixon, Dobbinson, Wakefield, Jamsen, & McLeod, 2008). Individuals continuously make the decision to expose their skin to UVR because they feel that a tan will make them look healthier and more attractive. This desire to maintain a consistent suntan has lead to the huge expansion of the indoor tanning industry. The International Tanning Association estimates that there are roughly 25,000 indoor tanning businesses in the U.S., which, all totaled, account for $5 billion in revenue (2007).

Research has shown indoor tanning facilities to be much more common in colder and less sunny climates (Palmer, Mayer, Woodruff, Eckhart, & Sallis, 2002). Areas that experience a higher average UV index (which is a measure of the intensity of solar UVR in a given area) typically have relatively few indoor tanning salons compared to lower UV index areas (Hoerster et al., 2009). It is assumed that this facility density is the result of a stable desire for a tanned appearance, at the population level, coupled with unfavorable weather patterns (Sayre & Dowdy, 2003). While outdoor tanning, or sunbathing, is dependent on weather conditions (Cafri, Thompson, Jacobsen, & Hillhouse, 2009), indoor tanning is always available. There are two potential problems with the availability assumption as the reason tanning individuals choose indoor tanning. Only 36% of individuals who use sunless tanning methods report doing so because weather conditions did not allow for a natural tan (Brooks et al., 2006). In addition, when summer brings continuously sunny days, research shows that, on average, indoor tanning decreases but it does not disappear (Vannini & McCright, 2004).

While these findings highlight potential problems with the assumption that individuals indoor tan due to weather related availability of sunshine, they fail to sufficiently examine the influence that daily weather fluctuations might have on indoor tanning. Specifically, researchers have yet to examine the contemporaneous and lagged associations between weather conditions and daily reports of indoor tanning. Researchers have examined the extent to which weekend weather forecasts impact outdoor tanning and sun protective behaviors (Dixon, Hill, Karoly, Jolley, & Aden, 2007). In this study, participants were randomly assigned to one of three conditions: an intervention condition where they were provided weather forecasts with UV Index predictions for the coming weekend and sun protection messages, an intervention condition where they were only provided with weather forecasts with UV Index predictions, and a control condition where they were only provided weather forecasts without UV Index predictions. There were no differences the following weekend in sun protective behaviors (e.g., clothing coverage, sunscreen) and reported sunburns across groups (Dixon et al., 2007). While this study represents an important contribution to the understanding of the association between weather and tanning, there are several gaps in the literature that remain unaddressed. Specifically, research has yet to examine tanning patterns, particularly indoor tanning patterns, at a daily level in order to illustrate potential influence of previous day tanning on current day tanning. In addition, research has yet to examine the impact of daily weather conditions on daily indoor tanning at the group level. Moreover, these types of research questions are also well suited to person specific analysis of time series data.

A time series in person-specific analysis entails repeated measures of a system or individual on one or more variables of interest (Chatfield, 2004; Pagano et al, 2006). For the purpose of the current study, the term time series and references to intensive collection of data will refer to designs utilizing at least 50 data points, as recommended by Hamaker, Dolan, & Molenaar (2003). The focus of the current study is on the examination of the time series of college students' indoor tanning in relation to daily weather information. The study first examined the sequential dependency seen within individuals in terms of indoor tanning. Sequentially dependent data is evident when the association between the value of a variable at time *t* is significantly associated with the value of the same variable at time *t* - 1, *t* - 2, etc. (Monnet et al, 2001). Given a sequentially dependent process, the knowledge of an individual's behavior on previous days can be useful for predicting, and potentially intervening on, current day behavior. For example, the present study examined the extent to which tanning on day *t* - 1 predicted indoor tanning on day *t*. This was done at the group level, as well as individually, for each participant, as it was highly unlikely that findings at the group level would hold at the level of the individual (Molenaar, 2004). We hypothesized, however, that sub-groups of the sample would be observed with similar patterns of tanning over time. Illustrating patterns in actual tanning over time represents a novel contribution to the skin cancer prevention literature.

The next step in the current study was the examination of the extent to which the inclusion of daily weather conditions predicted the probability of transitioning from non-tanning to tanning at the daily level. For example, to what extent does the cloud cover/visibility on a given day affect the probability of transitioning from a non-tanning state to a tanning state on that day? In addition, the potential lagged relationship between previous day's weather and current day's indoor tanning was examined. Similar to the hypothesis regarding tanning patterns, we did not expect homogeneity in the effects of weather, but, instead, expected to see sub-groups of the sample with different patterns of associations. It was expected that a sub-set of the sample would show clear patterns of tanning that are unaffected by weather conditions, while other groups will be more influenced by environmental characteristics.

Method

Participants

Ninety-six female students from a medium sized, public university in the mid-Atlantic region of the U.S. were recruited as control condition participants in a randomized trial aimed at reducing the incidence of skin cancer (for a complete discussion of the intervention, see Hillhouse, Turrisi, Stapleton, & Robinson, 2008). Of these students, only those who reported at least 1 indoor tanning episode were retained. The final sample consisted of 54 students with an average age of 19.2 years (SD = 1.8). Approximately 56% of the sample perceived their family's socioeconomic status (SES) to be about average relative to their peers, while 30% perceived their family's SES to be moderately higher than most families. The sample was 48% freshmen, 41% sophomores, and 11% juniors; 46% lived on-campus, 30% lived in off-campus housing, and 24% lived at home; 17% reported belonging to a sorority.

Measures

Indicators of weather. Weather data for each day of data collection was obtained from Weather Underground (www.weatherunderground.com, 2009). The measure chosen to represent daily weather conditions in the current study was visibility in miles (indexing cloud cover and mist/fog in the air). This measure was appropriate for the current study, as it sufficiently captures the atmospheric conditions necessary for outdoor tanning. Figure 1 illustrates the time series of this measure over the 84 days of the current study. No seasonal pattern in visibility was observed. On approximately half of the days of the study (52%), the maximum visibility (≤ 10 miles) was observed (M = 8.94, SD = 1.48).

Indoor tanning. Participants completed daily reports of indoor tanning every two weeks from December 31 to March 24. Students were asked to report on the days in which they indoor tanned during a given week (i.e., December 31st to January 6th). The resulting time series' are 84 days long, which are relatively short but acceptable series for modeling a sparse process like daily indoor tanning (Hamaker, Dolan, & Molenaar, 2003). Daily tanning was coded discretely (0 = No, 1 = Yes). Figure 2 presents a graphical representation of the time series of four example participants.

Plan of analysis

The current study examined daily indoor tanning patterns using a series of Markov models to describe the participants' indoor tanning time series. Markov models can be thought of as special, restricted cases of the more general framework of hidden Markov Modeling (HMMs; Visser, Raijmakers, & van der Mass, 2009). HMMs posit that the time series of an individual or system can be efficiently modeled as a discrete number of unobserved states (Rabiner, 1989) and that current status is only dependent on the previous state occupied (i.e., HMMs are first-order functions; Jackson, 2007). The states in the current model are determined by the discretely coded tanning data. In HMMs, the number of unobserved states in the time series is often unknown a priori and are decided upon based on the relative fit of models with varying numbers of states. The estimated parameters of these models are (1) stability and transition probabilities, (2) observation parameters within state, and (3) initial probabilities (Visser et al., 2009). Stability probabilities represent the probability of being in state S_x at time t given being in state S_x at time t – 1, whereas transition probabilities represent the probability of being in state S_x at time t given being in state S_y at time t – 1. Observation parameters represent conditional means and/or probabilities of indicator variables within a given state. Initial probabilities represent the probability of being in State S_x at the initial time point (i.e., time 1). For the current study, the models were constrained to be manifest Markov models. First, since daily indoor tanning was defined as a 2 state process at the daily level (i.e., Tanning/No Tanning), a 2 state model was used for all analyses. A related second set of constraints were placed on the observation parameters. With a 2 state process defined, the probability of indoor tanning in the “Tanning” state was fixed to 1.00, and the probability of not indoor tanning in the “No Tanning” state was fixed to 1.00. Therefore, the primary parameters of interest for the models in the current study were the stability/transition probabilities.

The analyses in the current study proceeded through the following steps. First, the overall pattern of indoor tanning transitions and stabilities was modeled and interpreted at the group level (N = 54; t = 84 days; total data points = 4620 days). Second, individual Markov models were performed on the time series of each participant.

The transition matrices of the group- and individual-level models were then compared as a way to illustrate the utility of modeling tanning at the level of the individual. Once group- and individual-level patterns of tanning were established, the third step was to examine the average daily impact of weather conditions on daily indoor tanning by incorporating daily weather conditions as a covariate on the transition matrix. Specifically, current and previous day visibility predicted the probability of transitioning from the "No Tanning" state to the "Tanning" state. Finally, corresponding conditional Markov models were performed examining daily tanning and daily weather conditions at the individual level. Once again, the group- and individual-level results were compared. We hypothesized that the impact of weather conditions would be much stronger for a subset of individuals than for the population as a whole.

Each of these models was performed in R using the Multi-State Modeling package (msm; Jackson, 2007), which is a maximum-likelihood based program for estimating Markov, hidden Markov, and misclassification models. In the group-level unconditional Markov model, the stability and transition matrix was estimated using the observed tanning states for each individual on each day of the study, whereas the models incorporating weather covariates used the observed states and the time-varying weather conditions to estimate the transition matrix. The same estimation procedure was used for the person-specific Markov models.

Results

Tanning Descriptive Statistics

Participants reported indoor tanning on 16% of the days examined in the study (i.e., 741 of 4536 total participant days). The mean number of indoor tanning episodes engaged in across the 84 days of the study was 13.72 (S.D. = 10.44), with frequencies ranging from 1 to 40 episodes. Figure 3 provides a graphical illustration of the extent to which this sample varies in terms of frequency of tanning. Over 1/3 of participants reported tanning fewer than 6 times, which represents an average of approximately once every two weeks. In contrast, approximately a quarter of the sample reported tanning 24 times or more, which represents an average of twice a week.

Group-Level Unconditional Markov Model

The group-level Markov model fit the data well. The observed prevalences of daily indoor tanning were predicted well across the length of the study, as the majority (60%) of model residuals (i.e., observed vs. expected prevalences) was smaller than 5% (see Figure 4 for residual time series and histogram). Methods examining the differences in observed and expected frequencies/prevalences are common in studies using Markov models (Albert, 1991; Altman, 2004; Jackson, 2007) given the difficulty associated with defining absolute goodness-of-fit measures for these types of models (Visser, Raijmakers, & van der Mass, 2009).

As mentioned above, the group-level estimates of sequential dependency were of primary interest in the current study. Stability in the “No Tanning” condition (see Table 1), which is the probability of not indoor tanning on day t given no tanning on day $t - 1$, was .87. This stability in the “No Tanning” state was indicative of the relative infrequency with which indoor tanning appears to occur at the group level. This was supported by the relatively high probability of transitioning out of the “Tanning” state to the “No Tanning” state ($p = .68$). The corresponding stability coefficient for the “Tanning” state at the group level was .33. To elaborate, this means that the probability of indoor tanning on day t given tanning on day $t - 1$ was .33, which was more than twice the probability of tanning on any given day (16%).

Person-specific Unconditional Markov Models

Using the method of comparing observed to expected indoor tanning prevalence, the fit of each person-specific Markov model was good (i.e., $M_{\text{Obs – Exp}} < 1.5\%$). Once again, the person-specific sequential dependencies in indoor tanning were of primary interest. Examination of these sequential dependencies in the person-specific Markov models indicated substantial heterogeneity across individuals (see Figure 5), such that there was relatively wide variability in the transition and stability coefficients observed at the level of the individual. Results indicated that, across individuals, there was no relationship between the probabilities of transitioning into the “Tanning” state and transitioning out of the “Tanning” state (r = -.12, p = .39; see Figure 5 for scatter plot and best-fit line).

The potential problems associated with group-level estimates of longitudinal processes were clearly illustrated by examining the differences that existed between individual patterns of tanning over time and the group-level pattern. While the group-level estimates do an acceptable job of representing the indoor tanning patterns of some of the participants, relatively salient discrepancies where illustrated for others. For example, a subset of the sample (n = 17) had transition probabilities from the “Tanning” state to the “No Tanning” state that were perfectly deterministic (i.e., *p’s* = 1.00). Five of these participants reported only a single tanning episode, which would naturally induce a transition probability of 1.00. The majority of the remaining individuals with transition probabilities equal to 1.00 (9 of 12) also indoor tanned relatively infrequently (i.e., 2 - 6 episodes), which made it unlikely that they would ever tan on consecutive days (i.e., stability = .00). The remaining 3 participants within this subset tanned much more frequently (i.e., 11, 12, and 23 episodes, respectively), which indicated a potentially deliberate pattern of non-consecutive day indoor tanning (e.g., every other day tanning, weekly pattern).

Another subset of the sample (n = 10) demonstrated stability coefficients for the "Tanning" state greater than or equal .50, which was much higher than the group-level stability coefficient (p = .33). Nine of these individuals reported 11 or more indoor tanning episodes (range = 4 – 40; Median = 22). In general, these stabilities indicated that individuals in this subset have at least a even probability of tanning of day t given tanning on day $t - 1$, with some individuals having a much higher probability (i.e., p's = .77 and .90).

Group Level Markov Model with Weather Covariates

As mentioned above, current and previous day weather conditions were included in the model as predictors of the transitions into the "Tanning" state from the "No Tanning" state. Given the relatively short length of the time series' examined and the expected small effect sizes, current and previous day weather were included in the model separately to avoid further reduction in statistical power. When examined at the group-level, the inclusion of current day weather as a covariate on the tanning transition matrix did not significantly improve model fit (likelihood ratio test $_{df = 1}$ = .74, p = .39). On average, the atmospheric clarity on day t had no impact on the probability of transitioning into the "Tanning" state on day t. This finding was supported by the mean visibility comparison on "Tanning" days and "No Tanning" days that showed nearly identical means ($M_{Tanning} = 8.94$, $M_{No\ Tanning} = 8.96$; see Table 2). Similar results were observed with the inclusion of previous day weather as a covariate (likelihood ratio test $_{df = 2} = 1.12$, $p = .29$). On average, the atmospheric clarity on day $t - 1$ had no impact on the probability of transitioning into the "Tanning" state on day t. Once again, this finding was supported by the mean visibility comparison on days *before* "Tanning" and "No Tanning" days that showed nearly identical means ($M_{Tanning} = 8.92$, $M_{No\ Tanning} = 8.94$).

Person-specific Markov Models with Weather Covariates

In order to examine the impact of weather on indoor tanning at the level of the individual, a series of conditional Markov models were performed for each participant. For those participants who indoor tanned 2 or fewer times across the length of the study, there was not enough information for these conditional Markov models to converge and provide interpretable estimates, so they were excluded from the analyses. For the remaining participants ($n = 45$), current and previous day weather conditions were again included in the model as predictors of the transitions into the "Tanning" state. Regarding current day weather, findings were similar to those from the group-level analysis for the vast majority of students ($n = 44$) , such that daily weather had no discernable impact on indoor tanning for the majority of participants (p's $> .05$; see Figure 6 for histograms of person-specific likelihood ratio test values for current and previous day's weather). However, for a single participant, the probability of tanning on a given day was strongly dependent on current day weather (likelihood ratio test $p < .005$; odds ratio = .56, $p < .01$) (see Figure 7 for histograms of person-specific covariate effects). For this individual, the probability of transitioning into the "Tanning" state was negatively associated with current day weather, such that, for every 1 mile increase in visibility, the odds of indoor tanning on a given day decreased by a factor of .56. Therefore, this individual tended to transition to “Tanning” on cloudier days. Regarding previous day weather, similar to findings from the group-level analysis, daily weather had no discernable impact on indoor tanning for any of the participants (likelihood ratio test p’s > .12 *and* log-linear covariate estimate p’s > .10). For a small group of participants, the fit of the model was marginally improved with the inclusion of weather covariates ($n_{\text{Prev}} = 4$, likelihood ratio test p’s $\leq .10$), but the covariate point estimates were not significantly different from 0 (log-linear covariate estimate p’s > .10).

Discussion

The purpose of the current study was to detail the daily process of indoor tanning and to explore the potential influence of weather conditions on this daily tanning among a sample of college females using Markov models. While a small number of studies have examined daily ultraviolet radiation over time (for example: Thieden, Philipsen, Sandby-Moller, Heydenreich, & Wulf, 2004, 2005), to the authors’ knowledge, the current study represented the first attempt to describe the potential pattern, or sequential dependency, that exists in intensively collected indoor tanning time-series data. Similarly, a small body of literature has touched upon the association between tanning and weather (for example: Cafri, Thompson, Jacobsen, & Hillhouse, 2009; Dixon et al., 2007; Hoerster et al., 2009; Palmer, Mayer, Woodruff, Eckhart, & Sallis, 2002; Vannini & McCright, 2004), but prior to the current study, no research had looked at the potential influence of daily weather conditions on daily indoor tanning.

Examining Daily Indoor Tanning

Results of the current study indicated that there was substantial heterogeneity in the sequential dependencies seen between indoor tanning on days t and $t - 1$. Group-level estimates indicated that the probability of indoor tanning was nearly three times as great when individuals indoor tanned on the previous day than when they had not. This finding implies that, on average, indoor tanning is a behavior that tends to occur in brief clusters, with no tanning occurring on the majority of days. This group-level result is in accordance with and provides a degree of empirical validation for research by Hillhouse and colleagues (2007) that found that the majority of college female indoor tanners report that they primarily tan before major social events (e.g., Spring Break, formal dance). Motivations to achieve a tanned appearance for these events would likely lead to tanning on two or more consecutive days prior to the event, which would increase the stability coefficient for the "Tanning" state.

While these group-level results demonstrate a degree of convergence with previous research, even further convergence can be seen between the person-specific findings and previous research (Hillhouse et al., 2007; Pagoto, McChargue, Schneider, & Worth Cook, 2004). The majority of the sample was relatively well represented by the group-level estimates, with most students demonstrating high stabilities (> .80) in the "No Tanning" state and low transition probabilities from the "No Tanning" state to the "Tanning" state (< .20). These probabilities are largely the result of relatively infrequent indoor tanning among many of the participants. These findings are supported by previous research (Knight et al., 2002) showing that the average college-age female tends to indoor tan relatively infrequently. However, both prior research (Knight et al., 2002; Poorsattar & Hornung, 2007) and the current study indicate that a minority of students engage in much riskier levels of indoor tanning. In the current study, these individuals had relatively high probabilities of tanning given tanning on the previous day, as well as relatively high probabilities of transitioning from “No Tanning” to “Tanning.” These students could be characterized as “Regular” indoor tanners (Hillhouse et al., 2007) or as “Moderate-to High-Risk” tanners (Pagoto et al., 2004) due to their high levels of intentional UVR exposure. Other individuals deviated from the group-level daily pattern by demonstrating very high probabilities of transitioning out of the “Tanning” state. Using the terminology from Hillhouse et al. (2007), these types of transition probabilities might be most common in “Spontaneous or Mood” tanners who tend to indoor tan when their friends are going to the tanning salon or who indoor tan to improve a negative mood.

These results regarding the daily patterns of indoor tanning among college-aged females highlight the unique utility of a person-specific approach (Molenaar, 2004) to the study of skin cancer risk, as well as the study of college risk, in general. A reliance on the group-level estimates when designing and refining intervention programs would obscure the heterogeneous risk observed across participants, as well as potential intervention mechanisms that might be most effective for targeted individuals. For example, for individuals who exhibit high stability coefficients within the “Tanning” state, it might be possible to reduce their risk for later skin cancer diagnoses by providing preventative materials (e.g., information on the health and/or appearance damaging effects of UVR exposure) *following* an indoor tanning episode. These materials might encourage students to transition to the “No Tanning” state more frequently, which would, ultimately, decrease the person-specific risk associated with UVR exposure. An adaptive intervention like this would be grounded in the harm reduction framework detailed by Marlatt (1996, 1998), where the ultimate goal is to eliminate a behavior, but more realistic and proximal goals are to reduce the risk associated with a given behavior. Tailored intervention strategies like these have the potential to show increased benefits for individuals and to be more efficient, in terms of resource allocation, than universal/one-size fits all programs that largely disregard person-specific risk (Offord, 2000).

Examining the Impact of Daily Weather Conditions on Daily Indoor Tanning

The current study went beyond describing daily patterns of tanning to examining potential daily influences on indoor tanning. Weather conditions have been discussed in the context of tanning salon density (Hoerster et al., 2009; Palmer et al., 2002), as well as in the context of predicting later tanning using forecasts (Dixon et al., 2007). However, prior to the current study, researchers had yet to examine the potential for daily weather conditions to impact daily indoor tanning. This research question was particularly relevant to the study of indoor tanning, and its associated risk for skin cancer, given the assumption that individuals choose to indoor tan due to the lack of potential for outdoor tanning (Brooks et al., 2006).

When examined at the group-level, there appeared to be no relationship between weather conditions and the probability of indoor tanning on a given day. This finding was not surprising considering that there is no *physical* mechanism by which indoor tanning access would be altered by weather conditions (i.e., indoor tanning, inherently, occurs indoors, away from any weather that might be occurring). The assumption that students choose to indoor tan due to a lack of favorable outdoor tanning conditions can also be considered tenuous given the practical advantages that indoor tanning has over outdoor tanning. For example, outdoor tanning requires extensive availability of time during daylight in which to devote to tanning, whereas indoor tanning requires relatively little time (e.g., 10 minutes of exposure) that can occur at any time throughout the day (i.e., evenings following class/work). The group-level null findings regarding weather were recapitulated in the person-specific findings for the vast majority of participants.

In general, as mentioned above, the hypothesis that a subset of the sample would show significantly stronger relationships with weather conditions than the group was not supported. There was only a single individual for whom the inclusion of weather conditions significantly improved model fit and significantly impacted the transition matrix. However, the relationship was quite strong for this individual, such that she tended to have a much greater probability of transitioning from “No Tanning” to “Tanning” on cloudier days than on clear day. The potential presence of this type of individual in the population of indoor tanners is supported by previous research that has found intentional UVR exposure to be associated with symptoms of seasonal affective disorder (Hillhouse, Stapleton, & Turrisi, 2005). Individuals with seasonal affective disorder tend to experience bouts of depression at specific times during the year, particularly during the poor weather months of the winter (Lurie, Gawinski, Pierce, & Rousseau, 2006). Another reason to suspect a link between weather and seasonal affective disorder is that light replacement therapy (exposing patients to high levels of artificial light) is one of the most efficacious treatments for depression related to seasonal affective disorder (Golden et al., 2005). Given that seasonal affective disorder tends to be under diagnosed (Lurie et al., 2006), it is possible that undiagnosed or affected but sub-syndromal students are self-medicating their depressive symptoms by indoor tanning. This explanation is supported by the above mentioned research that found a sub-group of individuals who were primarily motivated to indoor tan for mood and/or relaxation reasons (Hillhouse et al., 2007; Stapleton, Turrisi, Hillhouse, Robinson, & Abar, 2010).

Person-specific analyses, like those conducted in the current study, can be uniquely informative when examining potential motivations in applied behavioral research. Motivations to engage in a specific behavior are often heterogeneous across individuals. As mentioned above, interventions based solely on motivations observed at the group-level could potentially fail to address motivations held strongly by a minority of the population. Moreover, it is possible for individuals to be motivated or influenced by factors that that they are not consciously aware of (i.e., influence of daily weather). Theoretically and empirically guided person-specific analyses have the potential to illustrate these types of sub-conscious motivations that would not typically be observed in group-level research. Identifying and making individuals mindful of these potentially sub-conscious motivations might prove to be an efficacious method for reducing risk at the level of the individual.

Limitations and Future Directions

There are several limitations of the current study that should be mentioned. First, the sample was fairly small, consisted only of college-aged females, and came from a single university. Future study should seek to replicate the findings from the current study using a larger sample that is more representative of the population of indoor tanners, in terms of age, gender, occupation, and geographical location. A larger sample of indoor tanners might allow for a larger number/proportion of weather-affected individuals. Second, the person-specific time-series' examined in the current study were acceptable but relatively small. Future research should seek to follow participants over a longer period which would improve the power of the person-specific analyses performed. A related third limitation involves the use of weekly collection of daily indoor tanning data. While these collection methods have been shown reliable (Hillhouse, et al., 2008), it is possible that students made errors about the precise day that they indoor tanned (i.e., reported Monday but actually tanned on Tuesday). Future research should seek to collect tanning data on a daily basis to eliminate this concern. Daily collection would also allow for researchers to explore other potential influences on daily tanning, such as mood or upcoming social events. Fourth, it is possible that the weather data was not representative for some individuals on some of the days of the study, as some students may have not been at school or not in the area on some days throughout the study. This possibility is not particularly likely because the vast majority of students at the university from which the sample was collected were commuters from very close to campus or living in on-campus housing. Future research, whether employing weekly or daily data collection, might seek to ask participants to provide location information (e.g., zip code) for each day of the study to better pinpoint weather conditions. Finally, in order to better understand the potential for seasonal affective disorder to moderate the influence of weather conditions on daily tanning, researchers should include an accepted index for seasonal affective disorder symptoms (e.g., the Seasonal Pattern Assessment Questionnaire; Raheja, King, & Thompson, 1996) in their battery of measures at baseline. It would informative to know the extent to which seasonal affective symptoms are predictive of differences in probabilities of tanning on clear and cloudy days over time.

Conclusions

The current study was relatively novel in that it examined the daily patterns of indoor tanning, as well as the potential for weather conditions to affect indoor tanning, using both group-level and person-specific analysis. As is most often the case, group-level findings did not represent well the findings at the level of the individual (Molenaar, 2004). Person-specific analyses were well suited to the current study, as patterns of indoor tanning and the motivations for this tanning are likely to be highly idiosyncratic. The findings from the current study represent a first step toward understanding the process of tanning at the daily level and the ways in which external influences, specifically weather conditions, can affect this process. Moreover, the current study describes a methodologically rigorous analytic plan for identifying the daily risk behavior patterns and previously overlooked motivations to engage in these behaviors at the level of the individual. Existing and future interventions aimed at reducing risk for skin cancer can benefit from the results of the current study through the incorporation of adaptive materials at the daily level and/or through the use of similar person-specific methods examining motivations for later skin cancer diagnosis.

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Table 1

Group-level Stability and Transition Probabilities

		Day *t*	
		State 1 - Tanning	State 2 - No Tanning
Day *t* - 1	State 1 - Tanning	.33 (S.E. = .02)	.68 (S.E. = .02)
	State 2 - No Tanning	.13 (S.E. = .01)	.87 (S.E. = .01)

Table 2

Mean Current and Previous Day Visibility on Tanning and No Tanning Days

	Tanning	No Tanning
Current (Day *t*)	8.96	8.94
	(1.45)	(1.48)
Previous Day (Day *t* – 1)	8.92	8.94
	(1.43)	(1.49)

Figure 1

Visibility Time Series for the Length of the Current Study

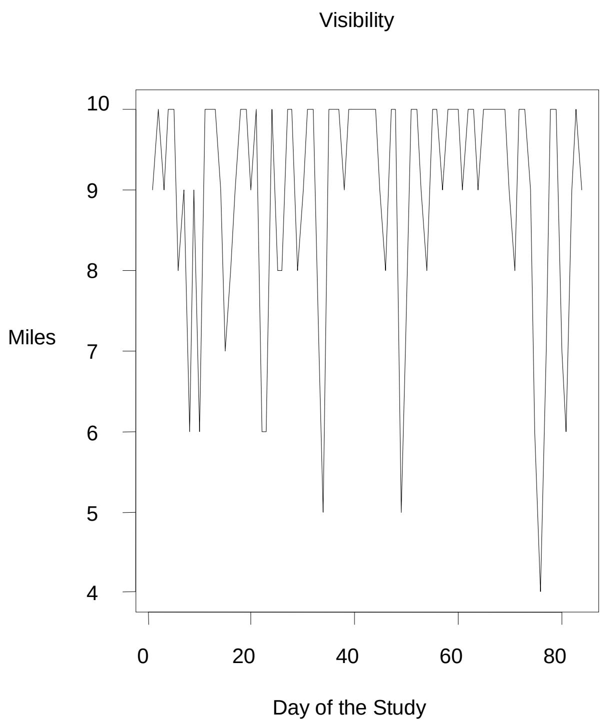


Figure 2

Example Tanning Time Series of 4 Participants

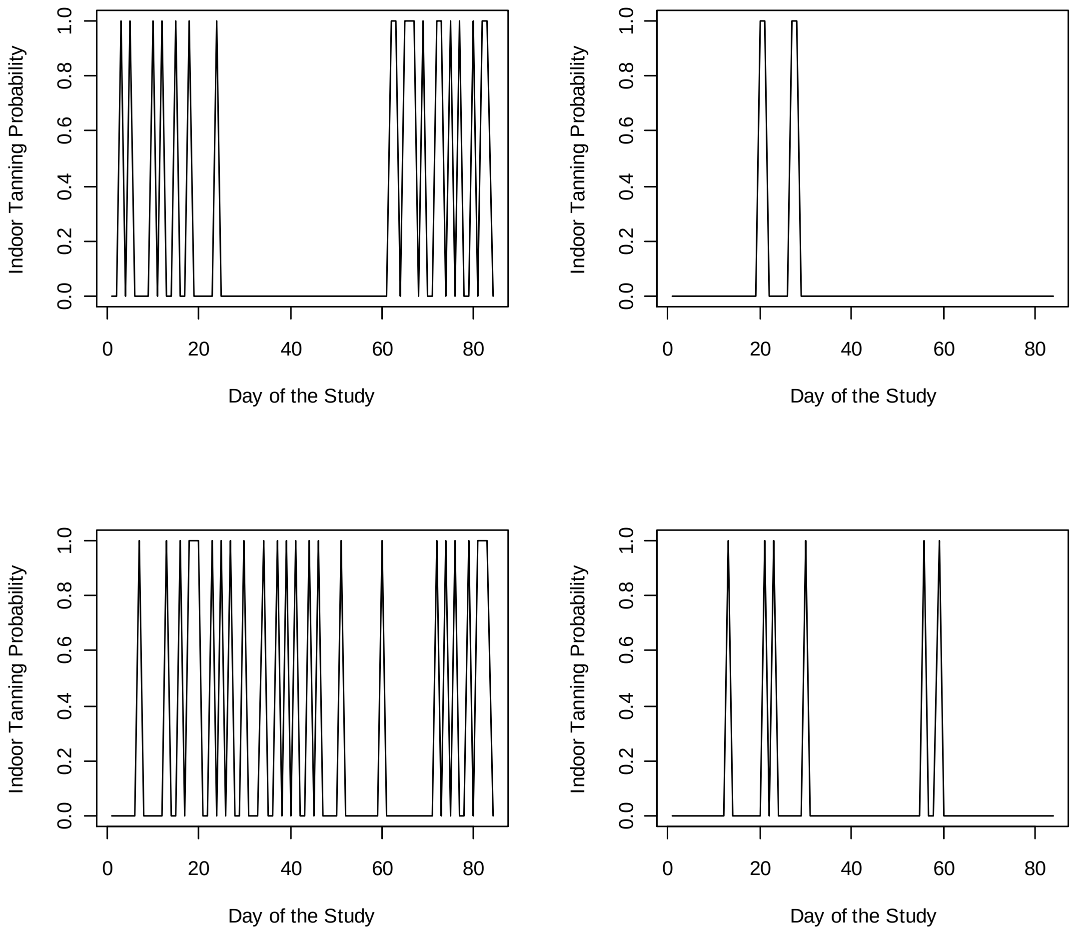


Figure 3

Frequency Histogram of Indoor Tanning Episodes Across Participants

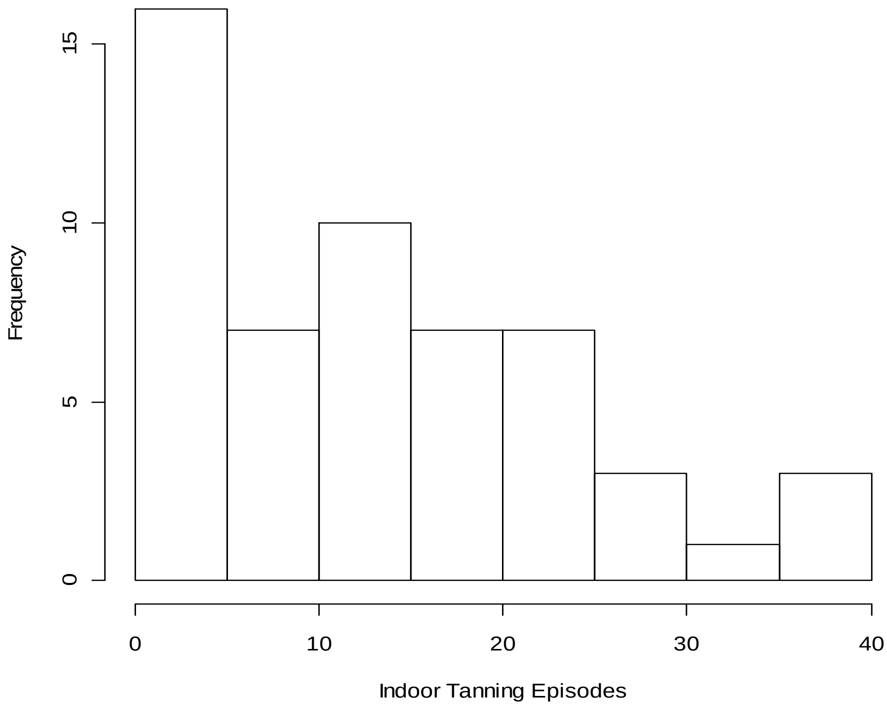


Figure 4

Group-level Markov Model Residuals

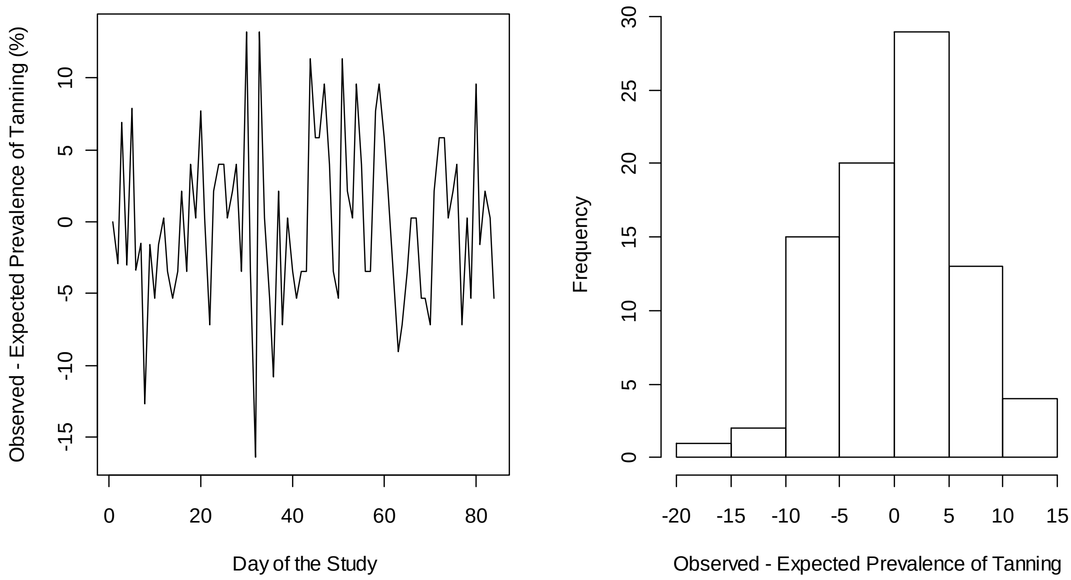
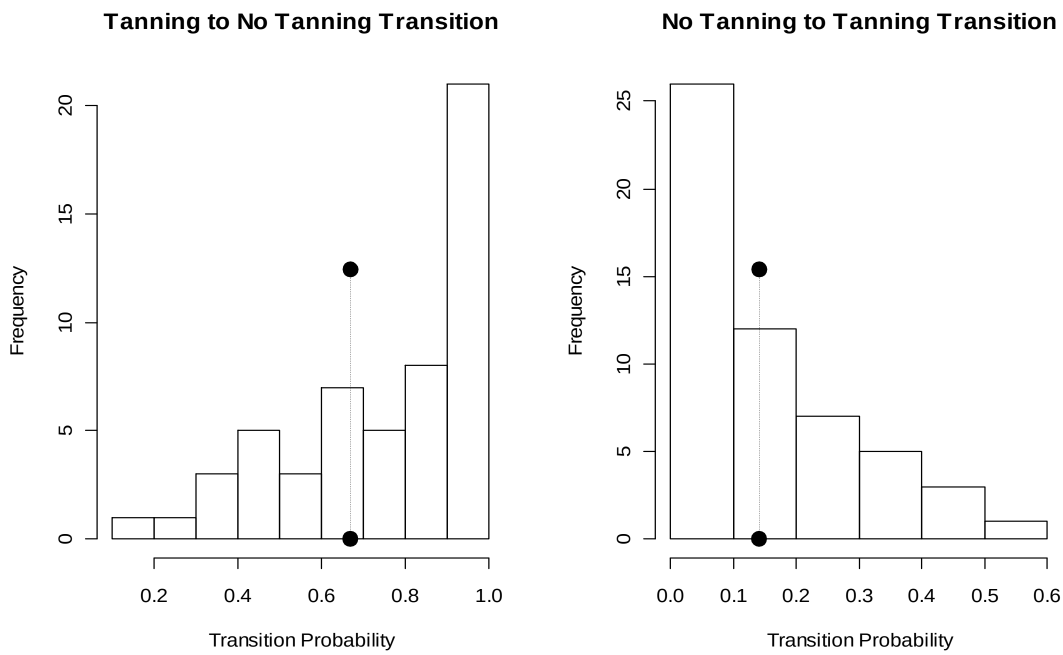


Figure 5

Histograms and Scatter Plot of Person-Specific Transition Probabilities



Note: Dashed lines represent group-level transition probability estimates.

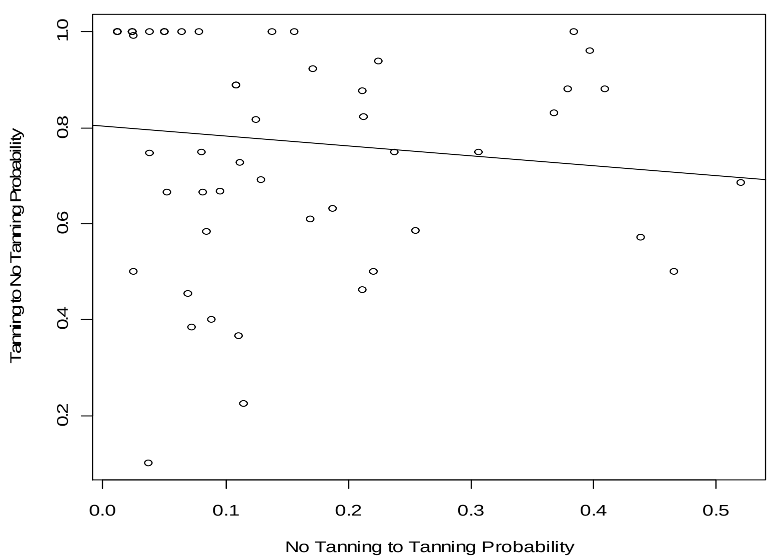


Figure 6

Person-Specific Likelihood Ratio Test Values Comparing Unconditional and Conditional Markov Models

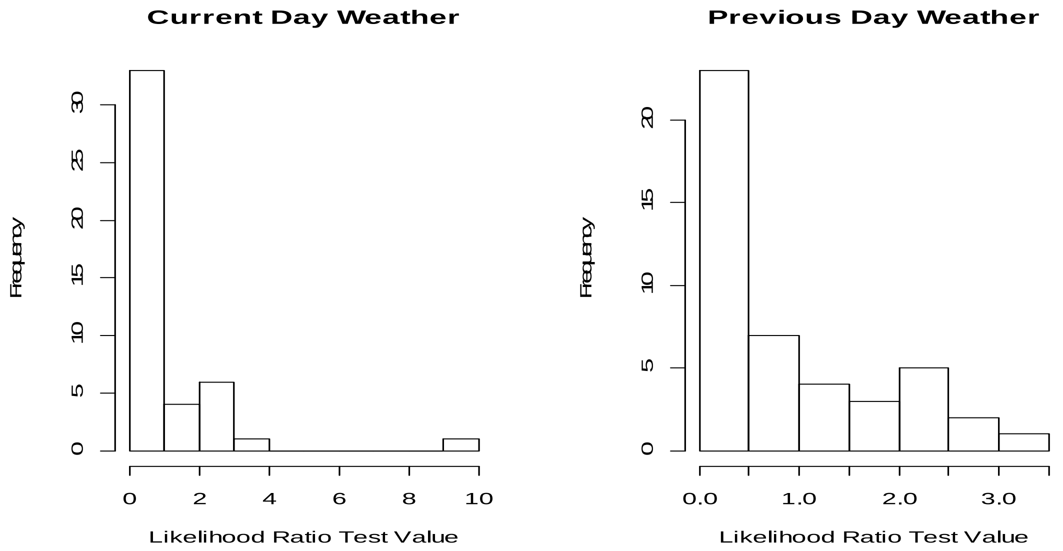
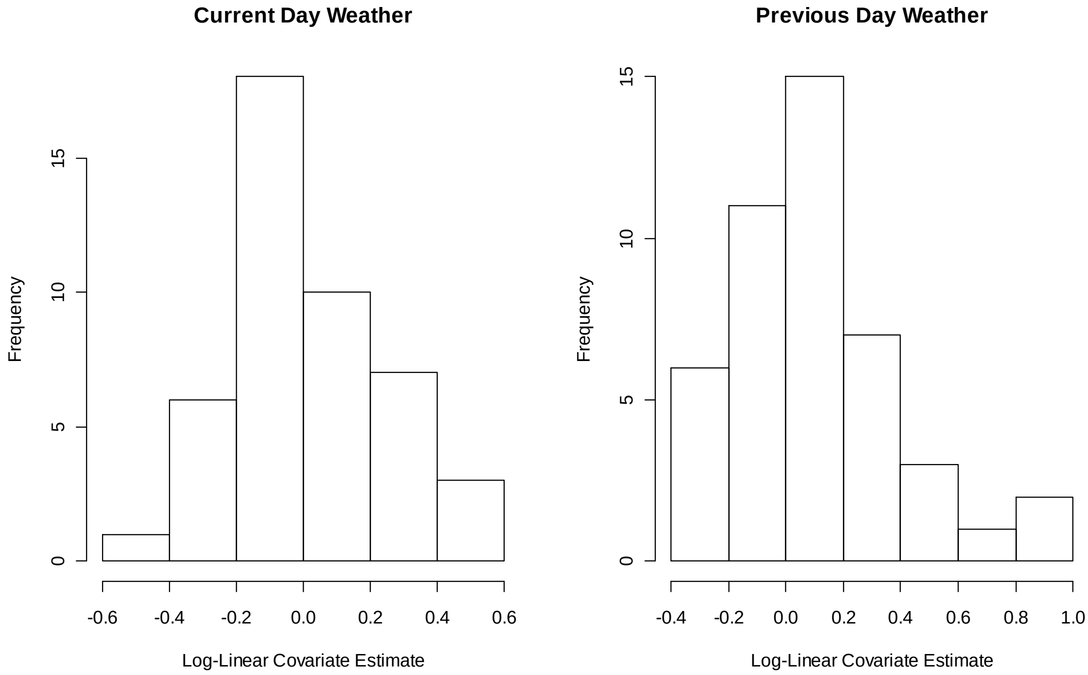


Figure 7

Person-Specific Log-Linear Covariate Effects



<u>Paper 3 - Preventing skin cancer in college females: Heterogeneous effects over time</u>

The incidence of skin cancer is on the rise worldwide (Geller & Annas, 2003; Katalinic, Kunze, & Schäfer, 2003), accounting for more new cancer cases than breast, prostate, lung, and colon cancer combined (ACS, 2008). In the United States alone, over one million new cases of basal cell and squamous cell skin cancer will be diagnosed, in addition to roughly 62,500 new incidences of melanoma (NCI, 2007). Skin cancer results in more than 11,000 deaths annually in the U.S., with melanoma responsible for more than 75% (ACS, 2008). The economic impact associated with skin cancer treatment in the U.S. exceeds $1 billion annually (Bickers et al., 2006; Chen et al., 2001).

A wealth of laboratory and epidemiological research has shown ultraviolet radiation (UVR) to be the leading cause of skin cancer (Atillasoy et al., 1998; Bennett, 2008; Hussein, 2005; Moan, Dahlback, & Setlow, 1999; Quinn, 1997), accounting for roughly 80% of all skin cancer diagnoses (Armstrong & Kricker, 1993). Understanding of its most common cause makes skin cancer one of the most easily preventable cancers in humans (Glanz & Mayer, 2005); avoiding prolonged exposure to UVR and using sunscreen with a skin protection factor (SPF) higher than 15 can greatly reduce the likelihood of skin cancer (Stern, Weinstock, & Baker, 1986; Thompson, Jolley, & Marks, 1993).

Despite the widespread knowledge of the risks associated with sun exposure and indoor tanning, intentional UVR exposure continues to rise (ITA, 2003). There has been a tremendous increase in the indoor tanning business, with the number of U.S. indoor tanners doubling to roughly 30 million over the past decade (ITA, 2007). Every day, close to 2 million Americans indoor tan, with marketing research indicating that 70% are white females between 16 and 49 years-of-age (Sun Magazine, 1997). This trend is particularly worrisome, as melanoma is the most common cancer among females ages 20 to 29 in the U.S. (Ries et al., 2008), with rates steadily increasing over the past several decades (Purdue, Freeman, Anderson, & Tucker, 2008). It is for these reasons that many researchers, practitioners, and policy makers have developed programs to prevent UVR exposure among this high risk subpopulation of adolescents and young adults (Emmons et al., 2008; Gibbons, Gerrard, Lane, Mahler, & Kulik, 2005; Hillhouse & Turrisi, 2002; Jackson & Aiken, 2006; Pagoto, McChargue, & Fuqua, 2003; Turrisi et al., 2004).

Early work on preventing skin cancer focused mainly on providing adolescents with knowledge about the health risks associated with UVR exposure (Castle, Skinner, & Hampson, 1999; Lowe, Balanda, Stanton, & Gillespie, 1999; Mermelstein & Rosenberg, 1992; Miller, Ashton, McHoskey, & Gimbel, 1990). Although these programs tended to show significant increases in adolescent knowledge of tanning risks, actual behavioral results were mixed. There are potential reasons why these programs failed to produce the desired behavioral change. First, research has consistently shown that individuals who intentionally tan tend to be sufficiently informed about the associated health risks (Robinson, Kim, Rosenbaum, & Ortiz, 2008). A second, related, reason for weak early results was the lack of attention paid to motivations for tanning. Research has shown the primary motivation for outdoor or indoor tanning is to improve appearance (Hillhouse, Stair, & Adler, 1996; Hillhouse, Turrisi, & Kastner, 2000; Jackson & Aiken, 2000; Miller et al., 1990). Alerting tanning individuals to known health risks does little to change perceptions of appearance and/or how tanning might enhance appearance.

More recent skin cancer prevention work has addressed motivations and has shaped messages around the appearance-damaging effects of UVR exposure, such as premature wrinkling, unsightly moles and freckles, and sunburns/peeling (Gibbons et al., 2005; Hillhouse & Turrisi, 2002; Hillhouse, Turrisi, Stapleton, & Robinson, 2008; Mahler et al., 2005; Pagoto et al., 2003). Most of these programs are grounded in the theory of planned behavior (Ajzen, 1991), which posits that attitudes toward a given behavior, perceptions about how significant others feel about the behavior, and the extent to which one perceives behavioral control over the behavior will predict intentions to engage in the behavior. These intentions will, in turn, predict actual engagement. By modifying attitudes toward the perceived benefits of tanning, intentions to tan would be diminished, as would actual tanning. Programs incorporating aspects of this model have produced much more promising results than previous prevention efforts.

Focusing on the efficiency and potential future dissemination of preventative efforts, Hillhouse and Turrisi (2002) designed and implemented a brief, 11-page workbook for female college students. The workbook described both the appearance damaging effects and the health risks associated with UVR exposure, with a particular emphasis on indoor tanning. This method is supported by protection motivation theory (Rogers, 1983), which states that persuasive messages that describe severe aversive consequences can be efficacious at preventing engagement in harmful behaviors. Hillhouse and Turrisi (2002) employed a general harm-reduction approach (MacCoun, 1998) in the development of the workbook; the overarching goal was the cessation of indoor tanning altogether, but, should individuals continue to tan, the goal was to encourage more protective tanning behaviors (e.g., reduce total exposure, wear more protective clothing when tanning, and/or always wear protective eyewear) (Hillhouse & Turrisi, 2002). In accordance with Jaccard's theory of alternative behavior (Jaccard, 1981), the workbook also detailed a variety of options, other than indoor tanning, that individuals could engage in that would satisfy the appearance-related motivations for tanning in a more healthy manner (e.g., exercise, fashion choices, sunless tanning products, etc.). Researchers found that the treatment group was largely willing to read the materials provided, and at follow-up two months post-intervention held less favorable attitudes toward indoor tanning, held more favorable attitudes toward appearance enhancing alternatives, intended to tan less, and intended to engage in more protective behaviors associated with UV exposure than control individuals (Hillhouse & Turrisi, 2002). Perhaps most importantly, the treatment group reported significantly fewer indoor tanning sessions over the prior 2 months than the control group.

An attempt to replicate the Hillhouse & Turrisi (2002) study recruited a larger, randomly assigned sample of college females from two geographically diverse universities in the eastern United States (Hillhouse, Turrisi, Stapleton, & Robinson, 2008). The previously used workbook was expanded to 24 pages and was professionally produced by a commercial art firm to improve the appearance of the materials. In order to take part in the study, students had to have tanned within the past year or report intentions to tan in the coming year. Students were interviewed during the fall, approximately 1 month later, and during the spring. Previous research had shown that tanning rates are lower during the fall and tend to increase during the spring months (Stapleton, Mastroleo, Ray, & Turrisi, 2008). The intervention buffered this seasonal increase, with the treatment group engaging in significantly fewer indoor tanning sessions during the spring (Hillhouse et al., 2008).

The purpose of the current study is to elaborate on these findings in three specific ways. Using data from the same randomized, intervention trial (Hillhouse et al., 2008), we will compare the trajectories of indoor tanning of the treatment and control conditions on a more fine-grained, monthly basis. While Hillhouse and colleagues (2008) showed the treatment group to have tanned less than the control group at the spring follow-up, it remains unclear whether the program effect is consistent through the winter and spring months or differs over the period. This issue is particularly relevant given the potential for the known seasonal trend in tanning to mask program effects. Given that the intervention consists of a single workbook, we anticipate an initial strong decrease in tanning followed by a mild decay of effects over time. Understanding how the intervention works over time might illustrate specific time points where additional materials (e.g., booster workbooks, reminder emails) should be introduced. The current study will also provide greater understanding of the above mentioned normative seasonal increase in tanning from the fall through the spring.

The second part of the current study will examine potential heterogeneity within the treatment condition over time using a longitudinal mixture model. Mixture models, in general, subdivide a sample into latent categories based on a set of manifest indicators. Longitudinal mixture models (e.g., growth mixture modeling, latent transition analysis, longitudinal latent class analysis), in particular, create latent trajectories of change and stability based on a single or small number of indicators measured over time. It is reasonable to believe that differential trajectories of tanning will emerge. Previous survey research has found the population of college-age female tanners to consist of 4 subtypes: individuals who report tanning before specific events (e.g., formal dances, spring break, weddings), individuals who report tanning spontaneously and/or for mood reasons, infrequent tanners with mixed motivations, and individuals who report tanning regularly throughout the year (Hillhouse, Turrisi, & Shields, 2007). These subgroups were shown to differ on intentions to tan, normative beliefs about tanning, and favorable attitudes toward indoor tanning. Prevention research in other fields has shown the utility of mixture models to illustrate potential differences in program effects based on unobserved latent grouping (Graham et al., 1991; van Lier, Muthén, van der Sar, & Crijnen, 2004). Using longitudinal latent class analysis of tanning frequency, the current study aims to show subgroups of the population with differential patterns of tanning over time. We expect some correspondence between our potential classes and the groups found by Hillhouse and colleagues (2007), but the groupings are not expected to be identical given that we are employing a different grouping mechanism (i.e., mixture models instead of cluster analysis), we are examining heterogeneity in reported behaviors (i.e., tanning frequency instead of motivations), and we are examining patterns over time (i.e., 6 time points instead of multiple measures at a single time point).

The third part of the current study will examine predictors of the latent trajectories of tanning. Participant demographic information, such as age, socio-economic status, and sorority membership, as well as self-reported tanning patterns, were included as predictors of tanning class membership, as each of these characteristics has been shown to be associated with indoor tanning (Cokkinides, Weinstock, O'Connell, & Thun, 2002; Hillhouse et al., 2007; Dennis, Kim, & Lowe, 2008; Reyes-Ortiz, Goodwin, & Freeman, 2005). We expect that latent classes characterized by more risky tanning over time will be more likely to endorse the higher frequency self-report patterns (e.g., weekly year round tanning) than classes with less risky tanning behaviors. Since appearance motivations have been identified as the primary reason for indoor tanning and the intervention aims to change these beliefs, attitudes toward a tanned appearance were also included as predictors of class membership. We expect that classes characterized by riskier tanning over time will have individuals with more favorable attitudes toward a tanned appearance than less risky tanning classes. By understanding baseline characteristics that influence program efficacy over time, researchers may be able to refine the workbook materials or the method of delivery to enhance effects.

Method

Participants

A random sample of 1690 female college students was selected from the student populations of two large universities in the eastern United States. Roughly half of those selected (n = 853) responded to an email invitation and screening survey. Inclusion criteria of either indoor tanning in the past year and/or having above average (5 or higher out of 7) intentions to indoor tan in the next year was met by 53% of respondents, of whom 95% agreed to participate. The final sample consisted of 379 female students randomly assigned to a treatment (n = 175) or control condition (n = 204). The average participant age was 19.23 (*S.D.* = 3.46), with 82% of the sample being between the ages of 18 and 19. Approximately 54% of participants reported their families to be of average socioeconomic status, with an additional 33% perceiving above average status relative to other families. Roughly 58% of participants were in their freshmen year of college; 33%

were sophomores and 8% juniors. Approximately 13% of participants reported being a member of a sorority. Preliminary analyses indicated no significant differences in age, perceived SES, class status, and sorority membership between intervention conditions.

Measures

Indoor tanning frequency. Participant indoor tanning was measured six times, at one month intervals, across the fall and spring semesters. For October, November, and March participants were asked to provide estimates of how many times they had indoor tanned in the last month. Retrospective self-reports of indoor and outdoor tanning have been used in the majority of previous research (e.g., Dennis. Kim, & Lowe, 2008; Hillhouse & Turrisi, 2002; Mahler et al., 2005; Pagoto et al., 2003). For December, January, and February, participants were asked, on a weekly basis, to indicate on which days in the past week they indoor tanned (which were then tallied to form weekly estimates). Four consecutive weekly tallies were summed to create monthly estimates (e.g., weeks 1 - 4 = December). Previous studies have shown weekly diary measures to have strong concurrent validity with more global, retrospective measures of indoor tanning, such that correlations between the diary tanning measures were strongly associated with monthly retrospective reports (r’s between .77 and .86; Hillhouse et al., 2008).

Self-reported indoor tanning patterns. Participants were asked to rate themselves on five hypothetical patterns of indoor tanning usage. The prompt for each of the 5 items was “I indoor tan…”, and the items being rated were: “occasionally, for example when some of my friends go I might go along” (labeled occasionally), “only before certain events such as formals, important dates, before spring break, before the start of the summer, etc" (labeled event tanning), "regularly, 1-7 times each week (or every other week) during particular seasons" (labeled seasonally), "regularly, 1-7 times each week (or every other week) all year long (more or less)" (labeled year round), and "irregularly, as I need it, but not event tanning as described above" (labeled irregularly). All items were on a 5-point Likert scale from strongly disagree to strongly agree. The average inter-item correlation magnitude of the 5 items was .18, with the strongest correlation being .56. Due to the low internal consistency between the items, they were introduced individually in subsequent analyses.

Attitudes toward a tanned appearance. Participants responded, on a 5-point Likert scale from strongly disagree to strongly agree, to 5 items regarding attitudes toward a tanned appearance ($\alpha = .82$). Items were as follows: "I look more attractive when I have a nice tan," "A tan can make me look thinner and more attractive," "I look more attractive with a tan because it hides skin flaws and blemishes," "Other people find me more attractive when I have a nice tan," and "A nice tan gives me a healthy, outdoor look." Items were summed to create a composite index of attitudes toward a tanned appearance, with higher values indicating more favorable attitudes.

Procedure

Following informed consent and randomization to condition, participants completed the baseline assessment (October) from which initial indoor tanning in the past month was collected, along with all demographic and covariate information. Participants in the intervention condition were then provided with the workbook described below and were asked to provide feedback on the materials one month later, as a way to ensure they were reading the intervention materials. At this 1-month follow-up, participants again provided estimates of past month indoor tanning frequency. Over the next 3 months, participants provided diary measures of indoor tanning, as discussed above. One month following the diary measures, participants were again asked to estimate their frequency of indoor tanning in the past month.

Contents of the Intervention

The workbook was professionally illustrated, 24 pages long, and sub-divided into 6 sections: (1) historical perspective on tanning, (2) current normative beliefs about tanning, (3) the health effects of UVR on skin tissue, (4) specific issues associated with indoor tanning, (5) guidelines for decreasing indoor tanning, and (6) alternative ways to enhance appearance (for more detail about the development and content of the workbook, see Hillhouse et al., 2008).

Plan of Analysis

Initially, a 2 (Group) X 6 (session) mixed-measures analysis of variance (ANOVA) was performed on self-reported tanning to examine the effects of the intervention over time. Polynomial trends were compared across groups, as were means at each of the six time points, in order to illustrate differential patterns across condition. For the second part of the study, longitudinal latent class analysis was used to demonstrate different patterns in tanning over time. Longitudinal latent class analysis can be a useful tool for examining trajectories of discontinuous change over time and has been used in previous prevention related research (Lanza & Collins, 2006), but has not yet been employed in the study of indoor tanning prevention. The classes from the treatment condition were compared to the classes in the control condition as a way to check whether the intervention had a qualitative effect on the types of tanners in the treatment group or, instead, a quantitative effect on the extent of indoor tanning within the classes. Finally, demographic characteristics, self-reports of tanning patterns, and attitudes toward a tanned appearance were included as covariates to show whether baseline characteristics can predict latent patterns of tanning over time.

Results

Preliminary Analyses

Group mean indoor tanning across the six time points were tallied and plotted by intervention condition (see Figure 1). As expected, both groups show an increase from the fall through the spring. The distributions of each group at monthly data point were positively skewed, with a preponderance of zeroes. Consequently, the percent of participants reporting no tanning for each time point was also calculated (see Figure 2). Following the intervention, there were more tanning abstainers among the treatment individuals than among the controls at each time point. Based on group by abstainer status, only the differences seen in December and January were significant, $p < .05$.

Comparisons over Time

Results of the mixed-measures ANOVA, using the Huynh-Feldt correction for departures from sphericity on the effects involving the repeated constructs, revealed a significant main effect of time, $F\ (3.36, 1158.07) = 17.53$, $p < .001$. There were significant linear, $F\ (1, 345) = 32.85$, $p < .001$, and quadratic trends, $F\ (1, 345) = 8.59$, $p < .01$, in the data. In general, there appeared to be a significant increase over time in indoor tanning frequency, which is less pronounced across the middle 4 months (for a visual representation, see Figure 1).

There were significant between group differences in the quadratic, F (1, 345) = 4.45, $p < .05$, and cubic trends, F (1, 345) = 4.27, $p < .05$, as well as a difference in the linear trend that approached significance, F (1, 345) = 3.41, $p < .07$. It appears that the treatment condition experienced a deeper dip in indoor tanning than did the control individuals. In addition, the increase following the dip in tanning was steeper for the control group than for the treatment group. Finally, the general increase in tanning from the fall to the spring was less pronounced for the treatment group than for the control group. Each of these findings shows the treatment condition to have better tanning behavior than the control condition. The most marked tanning benefits for treatment participants were observed during the middle two months and the final time point. Overall, the benefits of receiving the intervention are consistent with the results seen in the initial evaluation of the program by Hillhouse et al (2008).

Examining Differences within the Treatment Group

In order to more fully understand the effects of the intervention, we analyzed potential heterogeneity within the treatment group over time using a longitudinal model. Latent class analysis divides a population into sub-groups based on discrete responses to repeated measures of a single or multiple constructs. Longitudinal latent class analysis was chosen over longitudinal latent profile analysis or growth mixture modeling (Muthén & Muthén, 2000) because the later two models are most commonly used with continuous indicators. Although the measures of tanning used in the study were continuous, the large number of zeroes and the positive skew at each time point resulted in estimation difficulties when treating the variables as continuous. Therefore, tanning was categorized into meaningful bins. The categories were: never tanned (0 occasions), no more than once a week (1 - 4 occasions per month), up to twice a week (5 – 8 occasions), and more than twice a week (9+ occasions). Categorization resulted in relatively little loss of information, as the correlations between the continuous and categorical indicators for any month were greater than .90. The above mixed measures ANOVA was substantively identical when using the raw, continuous data and the discretized data.

A subgroup of the treatment condition abstained from indoor tanning across all time points (n = 57). To simplify the analyses, this subgroup was removed from the longitudinal latent class analysis and treated as a separate, manifest subgroup. A series of longitudinal latent class models were then run with the 118 treatment participants who reported tanning at least once across the six time points. Based on the Bayesian Information Criteria (BIC) and the adjusted likelihood ratio test (Lo, Mendell, & Rubin, 2001), a two class model appears to provide the best fit to the data. Simulation research has shown the BIC and aLRT to be trustworthy fit statistics for latent class models (Nylund, Asparouhov, & Muthén, 2006).

The first latent class, representing approximately 37% of the sample, consisted of individuals with a relatively low probability of abstaining at any given point, coupled with an increased probability of tanning at least twice a week (see Table 1). This class was labeled heavy tanners. Although the probability of more risky tanning (e.g., tanning twice a week or more) tends to increase, it never exceeds .52 for “up to twice a week” and .33 for “more than twice a week.” The second latent class, accounting for roughly 63% of the sample, was labeled the moderate tanner class and was made up of individuals with a much higher probability of abstaining from indoor tanning at any time point than the first class. The moderate tanner class also exhibited very low probabilities (< .10) of tanning "up to twice a week or more." When individuals in this class begin tanning, they primarily transition to indoor tanning "no more than once a week."

Impact of the Intervention on Sub-Groups

In order to further understand the impact of the intervention on sub-groups of the population, we also ran the longitudinal latent class model in the control group. Comparing classes solutions across intervention condition may provide further insight into program effects among latent sub-groups of the college female tanning population. Similar to the treatment group, a portion of the control condition abstained from indoor tanning across all time points (n = 60); the proportion was slightly higher in the treatment condition (i.e., 33% vs. 29%). As in the treatment condition, these individuals were not included in the latent class analysis. A two-class solution was also shown to provide the best fit in the control condition. Moreover, the classes in the control condition appear to be the same as those seen in the treatment condition (see Table 1). Performing a two-group longitudinal latent class analysis revealed that, according to the AIC and BIC, the latent class probabilities were identical in each condition (i.e., 37% and 63%).

The first class in the control condition (37%) was also labeled heavy tanners and characterized by relatively low probability of abstaining at any given point, as well as increasing probabilities of tanning "up to twice a week" and "more than twice a week." The second class (63%) also bears a striking resemblance to the moderate tanners in the treatment condition, with higher probabilities of abstaining than heavy tanners and less likelihood to transition to more risky tanning.

Although the solutions in the treatment and control group were structurally similar, there were important differences. For example, when holding tanning probabilities equal across condition, there was a significant decline in model fit, likelihood ratio χ^2 (38) = 58.82, $p < .05$. Heavy tanners in the treatment condition exhibited lower probabilities of high frequency tanning (e.g., “more than twice a week”) at later time points than heavy tanners in the control condition. For example, at the final time point, heavy tanners in the treatment condition had a .30 probability of tanning “more than twice a week,” whereas the control condition had a probability of .58. For moderate tanners, it appears that treatment individuals had a higher probability of abstaining from indoor tanning across time. This difference was most pronounced between November and January, where the average probability of abstaining was .74 for the treatment group and .54 for the controls.

Overall, based on the observed proportions of the manifest abstainer class and the two latent classes, the intervention does not appear to change the type of pattern an individual will take. Instead, the intervention appears to decrease the probability of more high risk tanning for some (heavy tanners), while increasing the probability that an individual will abstain at any given point for others (moderate tanners). These results are consistent with the harm reduction approach to preventative interventions (MacCoun, 1998).

Identifying Predictors of Tanning Classes

With the identification of three types of tanners in the treatment condition, we next focused on identifying covariates, collected in October, which might predict a person would be an abstainer, heavy tanner, or moderate tanner. For the subsequent analyses, we classified students into their most likely classes. The average student-specific probability of class membership was .97 and .96, respectively, indicating that individuals were classified with a high degree of certainty. Due to the high posterior probabilities, the degree of bias due to classification error is likely small.

Logistic regression was performed with participant demographic variables (participant age, perceived socio-economic status, and sorority membership status), self-reports of tanning patterns, and attitudes toward a tanned appearance predicting class membership. The abstainer class served as the reference group. The set of predictors significantly distinguished between the latent profiles, accounting for roughly 36% of the variance in group membership, Nagelkerke Pseudo $R^2 = .36$ (see Table 2 for group means and percentages).

Of the demographic variables, only age was a significant predictor. Participant age significantly predicted being in the abstainer group over the moderate tanning class, $\beta = -.13$, $p < .05$. For every additional year of age, the odds of being in the abstainer group rather than the moderate tanning class increase by 1.14.

Of the self-reported patterns of indoor tanning, occasional and year round tanning were shown to significantly distinguish between latent patterns of tanning over time. Occasional tanning was shown to significantly distinguish between the abstainer group and moderate tanners, $\beta = .35$, $p < .05$. For every unit increase in reported occasional tanning, the odds of being in the moderate tanning class over the abstainer group increased by 1.41. The distinction between the abstainer group and the heavy tanning class based on self-reports of year round tanning was significant, $\beta = .70$, $p < .05$. For every unit increase in year round tanning, the odds of being a heavy tanner over the abstainer group increased by a factor of 2.02. The effects of self-reports of seasonal tanning and attitudes toward a tanned appearance on the distinction between abstainers and the heavy tanning class approached significance (β = .42, *p* = .06; β = .18, *p* = .05, respectively). For every unit increase in self-reports of tanning, the odds of being in the heavy tanning class over the abstainer class increased by 1.53. For every unit increase in attitudes toward a tanned appearance, the odds of being in the heavy tanning class over the abstainer class increased by 1.20. In general, it appears that abstainers only tend to report event tanning patterns, whereas the other two classes also report relatively high spontaneous and seasonal tanning (see Table 3). In addition, the heavy tanners reported relatively high year round tanning. The two tanning classes also appear to hold more favorable attitudes toward a tanned appearance than the abstainer group.

Discussion

Introducing college-aged females to intervention materials cataloging the appearance-related negative consequences of indoor tanning, as well as appearance-enhancing alternatives to tanning, can have an impact on indoor tanning from the fall through the peak tanning times of the spring. On average, those who received the intervention experienced a significantly stronger decrease in indoor tanning frequency across the winter months than the control group. Furthermore, during the spring months, where an increase in tanning is normative (Stapleton et al., 2008), those who were given the intervention workbook tended to indoor tan significantly less. This difference is potentially crucial since the final time point of the study coincides with college Spring Break, an event that has been associated with increases in indoor tanning (O'Riordan et al., 2006). While the intervention does not appear to eliminate indoor tanning, it does suggest that the harm-reduction strategy employed (Hillhouse & Turrisi, 2002; MacCoun,

1998) was successful at reducing student risk for skin cancer. This is particularly encouraging given the relatively brief and innocuous nature of the intervention.

To further understand the preventative effects of the intervention, we examined differences in tanning trajectories within the treatment group using a relatively novel analytic approach. Three patterns of tanning existed within the treatment group. The first group abstained from indoor tanning across the entire length of the study. These students were less likely to endorse seasonal or year round patterns of tanning and seem to most closely resemble the event tanners discussed in Hillhouse et al (2007). While it is difficult to determine whether the intervention had an effect on these students due to unknown tanning that occurred both before and after the study, there was a higher proportion of abstainers in the treatment group than the control group (32% vs. 29%). Replication with a larger sample is needed to show the utility of the intervention to increase tanning abstinence.

The second group, labeled heavy tanners, consisted of women who showed a relatively consistent increase in tanning across the study. These participants had a relatively low probability of abstaining from tanning at any given time point, with a relatively strong probability of tanning between 1 and 2 times a week. Heavy tanners were most likely to endorse seasonal and year round patterns of tanning, as well as have a relatively high prevalence of self-reported occasional and event tanning and highly favorable attitudes toward a tanned appearance. This self-report pattern is similar to the regular tanners seen in Hillhouse et al (2007). When comparing treatment heavy tanners to control heavy tanners, it appears that the intervention reduces the highest levels of tanning (i.e., more than 2 times a week). These findings are particularly encouraging, as this class, accounting for nearly a quarter of the sample, represents the riskiest tanners in the population.

The final group, accounting for approximately 40% of the treatment population, consisted of participants with relatively high probabilities of abstaining from tanning during the first half of the study that declined during the second half of the study. Although the probability of abstaining decreased across the second half of the study, moderate tanners tend to transition to relatively infrequent tanning (i.e., no more than once a week) more than individuals in the heavy tanning class. Additionally, when compared with their counterparts in the control group, treatment individuals in the moderate tanning class had a consistently higher probability of abstaining following the intervention. Individuals in this class tended to report high levels of event, occasional, and seasonal tanning, and they most closely resemble the mixed tanners seen in Hillhouse et al (2007). Seeing effects on this class of individuals is also encouraging, as they represent the most common segment of the college female tanning population.

In general, it appears that the intervention is successful at reaching each of the sub-groups of tanners that were seen in the current study. Both moderate and heavy tanners appear to experience harm reduction as the result of the intervention. These findings are important given the nature of the intervention. The workbook provided to students is aimed at college-age females who are currently tanning or plan on tanning in the coming year. As has been illustrated in the current and previous studies (Hillhouse et al., 2007), this population is fairly heterogeneous in perceived and observed patterns of tanning. Mixture models, such as longitudinal latent class analysis, represent a relatively new method by which prevention researchers can examine these potential latent differences. Knowing that the intervention is efficacious across sub-groups supports the notion of the workbook functioning as a universal prevention program (Offord, 2000) that can be provided to the population of female college students. The results of the current study also illustrate a potential mechanism by which program efficacy might be improved. By examining both the sample and class level patterns of tanning over time, it appears that indoor tanning declines until the fourth month, at which point participants begin tanning more often. It is possible that booster materials (e.g., short pamphlet, reminder emails) reinforcing the preventative messages found in the workbook could improve efficacy if administered at this juncture. Perhaps by reminding students of the appearance risks of and viable enhancement alternatives to indoor tanning several months after the intervention, more healthy patterns of behavior will be sustained. Similarly, enhancing dosage at the point of the initial intervention might enhance protection, particularly among those individuals who tan relatively infrequently. As mentioned above, the difference between treatment and control in the percentage of participants who completely abstained was small. By increasing the dosage of the intervention (e.g., additional handbook modules, adding an online interactive piece), it may be possible to increase abstinence rates among individuals for whom indoor tanning is less of an established pattern of behavior and further reduce the experienced risk of individuals who tend to tan more frequently. In addition, program efficacy might also be enhanced by performing the current intervention on younger students among whom indoor tanning behaviors are just beginning to emerge. Exposing students to the appearance-damaging effects of UVR exposure at the point in which they are beginning to consider tanning might foster increased abstinence and decreased lifetime risk.

While the current study provides important information about the heterogeneous effects of the intervention over time, there are several limitations that must be addressed. First, the sample was relatively small and consisted solely of women attending college. Future work may seek to replicate the findings from the current study with a larger sample that consists of women in college and those not attending college. Since the intervention materials are directed at indoor tanning, in general, with no particular focus on college specific issues, we would not expect noticeable differences in program efficacy between the two groups of women. Second, the length of the current study (i.e., 6 months) does not allow researchers to compare tanning, during the same time span (e.g., September 2006 vs. September 2007), before and after the intervention. Showing a significant decrease in tanning given this hypothetical contrast would strengthen the agreement for a sustained effect. However, it is important to note that a clear pattern of less risky tanning emerged among the treatment condition across the length of the study, even during the spring months when tanning was expected to increase. Future work should track program effects, as well as normative patterns of tanning, across the full length of the calendar year. Thirdly, the measures of indoor tanning frequency were collected using student self-reports. Future research might seek to verify self-reports using data from other sources (e.g., tanning solon accounts, reports of close friends or parents). Finally, since the intervention workbook did not specifically address outdoor tanning, or sun bathing, it is possible that participants who decreased indoor tanning substituted this UVR exposure for more traditional sun exposure. However, we do not expect that this is the case, as the workbook materials discuss the appearance damaging effects of UVR exposure in general, and participants who changed their indoor tanning to prevent these appearance outcomes would not be likely to expose themselves to alternative UVR.

Despite these limitations, the current study illustrates that a harm reduction focused, brief intervention can reduce risk for skin cancer among female college students through the fall and spring semesters. While the current study shows that this tanning population is heterogeneous, consisting of several sub-groups of tanners with different patterns over time, the intervention appears to have an observable preventative effect on each tanning group. Illustration and identification of these sub-groups may allow researchers to further enhance program effects by targeting the timing at which effects appear to be decaying among the groups to reinforce initial effects.

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Table 1

Group Conditional Probabilities of Tanning in the Past Month

	October	November	December	January	February	March
Treatment						
Heavy Tanners (37%)						
Never	.33	.31	.27	.05	.05	.00
No more than once a week	.28	.32	.30	.35	.12	.23
No more than twice a week	.17	.16	.20	.27	.52	.48
More than twice a week	.22	.21	.23	.33	.30	.30
Moderate Tanners (63%)						
Never	.60	.70	.79	.72	.46	.43
No more than once a week	.24	.26	.18	.25	.46	.48
No more than twice a week	.10	.03	.03	.04	.03	.04
More than twice a week	.07	.01	.00	.00	.06	.05
Control						
Heavy Tanners (37%)						
Never	.47	.40	.19	.10	.09	.03
No more than once a week	.21	.28	.25	.23	.22	.00
No more than twice a week	.13	.15	.30	.25	.30	.39
More than twice a week	.19	.17	.26	.43	.39	.58
Moderate Tanners (63%)						
Never	.70	.57	.53	.53	.37	.38
No more than once a week	.21	.37	.39	.30	.57	.46
No more than twice a week	.09	.06	.05	.12	.06	.16
More than twice a week	.00	.00	.03	.05	.00	.00

Table 2

Covariate Means or Percentages by Group

	Abstainers (32%)	Moderate Tanners (44%)	Heavy Tanners (24%)
Demographics			
Years-of-age	20.96 [a]	18.97 [a]	18.79
Socioeconomic Status	3.21	3.10	3.34
Greek Status	18%	7%	24%
Patterns of Tanning			
Occasionally	-.16 [a]	.50 [a]	.50
Event Tanning	1.10	1.22	.84
Seasonally	-1.14 [c]	-.37	.30 [c]
Year Round	-1.65 [b]	-1.32	-.42 [b]
Irregularly	-.47	-.28	-.84
Attitudes toward a tanned appearance	20.07 [c]	21.09	21.68 [c]

[a] significantly distinguished between moderate tanners and abstainers, $p < .05$

[b] significantly distinguished between heavy tanners and abstainers, $p < .05$

[c] approach significant distinguishing between heavy tanners and abstainers, $p \leq .06$

Figure 1

Mean Indoor Tanning Frequency by Group over Time

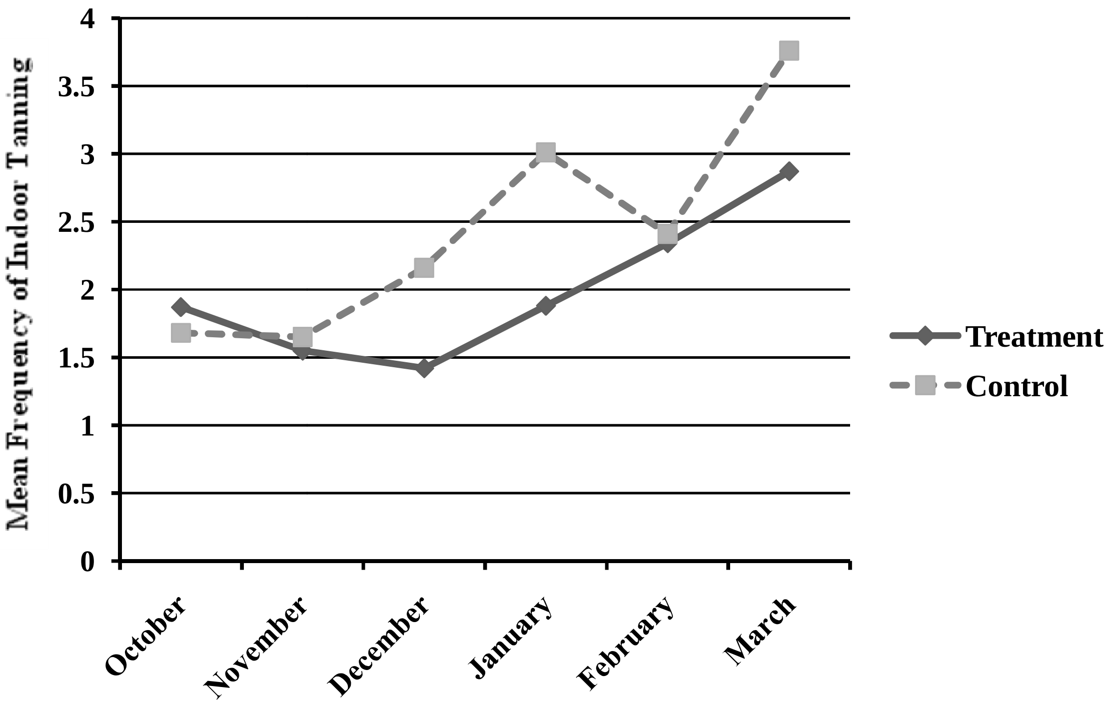
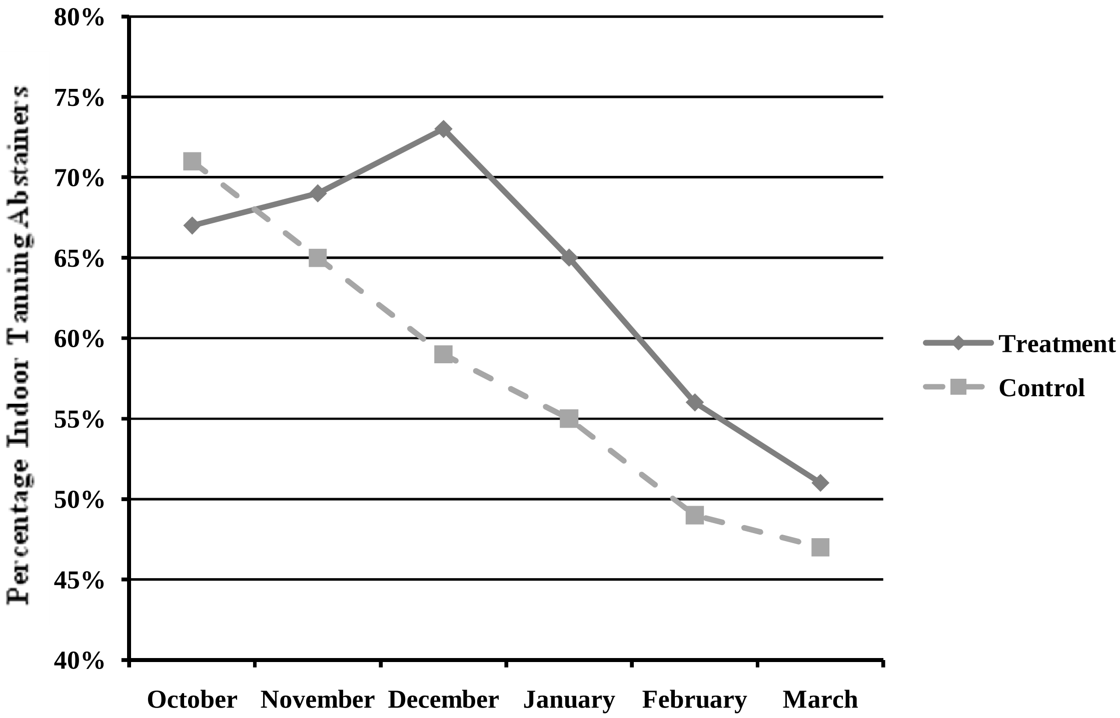


Figure 2

Astainer Rates by Group over Time



General Conclusions and Future Directions

This dissertation highlighted the utility and complexity associated with the examination of sample/population heterogeneity in the behavioral sciences. In many ways, researchers have only scratched the surface of what types of questions can be asked through the use of the above discussed mixture models and person-specific analysis. Our understanding of many of the most salient issues in applied research (e.g., risk/protective factors, motivations, intervention efficacy, sustainability, etc.) can be greatly enhanced through reexamination using these strategies. However, the desire and professional push to make use of these emerging methods has resulted in the substantive application of these methods without empirically defined guidelines for their use. Without the requisite foundational literature upon which to base analyses and their associated interpretations, new or inexperienced users of these methods may not always make the most appropriate decisions regarding their data. In addition to answering prevention-related questions of interest, the studies in the current dissertation sought to provide some of these methodological guidelines and examples for more substantively minded researchers.

The first study discussed the issue of identification of models in latent class analysis. While this topic has received some relatively recent attention in the methodological literature (Dayton, 1998; Formann, 2003; Magidson & Vermunt, 2001), few specific guidelines for practice have been provided. My dissertation made recommendations specific to models known to be non-identified, in addition to reiterating and applying a framework for deciding upon the maximum number of classes that would be appropriate to retain given the amount of information available in the model (Loken & Molenaar, 2007). These recommendations could potentially result in substantively-focused readers making more appropriate modeling decisions in latent class analysis, as well as when utilizing other mixture models. The first study also provided empirically derived estimates of the bias associated with the "classify-analyze" (Clogg, 1995) approach to examining distal outcomes in LCA. This preliminary contribution to this area of research was relatively novel, since to date, the majority of the discussion on this topic has failed to provide specific estimates of distal bias across varying situations (Clark & Muthén, under review: Hagenaars, 1993; Roeder et al., 1999).

The second study examined indoor tanning using group-level and person-specific Markov models. The analytic plan employed, including the group- and individual-level comparisons, can potentially serve as an approximate "roadmap" for researchers interested in examining this type of data (i.e., individual time series). One specific area of prevention research that might benefit from the use of Markov models (both unconditional and including time-varying covariates) is in drug and alcohol relapse prevention (Shirley, Small, Lynch, Maisto, & Oslin, 2010; Warren, Hawkins, & Sprott, 2003; Witkiewitz & Marlatt, 2004). The transitions into and out of "Sober" and "Using" states should be modeled at the level of the individual, as individuals seeking to quit substance use are heterogeneous in their patterns of success. Moreover, triggers that influence the transition into the "Using" state are likely to be idiosyncratic, necessitating the modeling of the process at the level of the individual. The plan of analysis for study 2 could easily generalize to this, and many other, applied situations.

The third study demonstrated the potential importance of acknowledging heterogeneity within the treatment condition of randomized, prevention trials. Specifically, this study showed that different latent classes of indoor tanners exist based upon their monthly reports of tanning frequency and that membership in these latent classes was associated with the type of impact the intervention in question had. Prevention scientists can make use of this study as an example of a method for probing the heterogeneous effects an intervention can have based on an unobserved, categorical variable. In addition, the third study also illustrated the use of longitudinal latent class analysis, which can function as an alternative to the more commonly used latent class growth analysis (Nagin, 1999) and growth mixture modeling (Muthén & Muthén, 2000) for categorical outcomes measured over time.

Future Directions

One potential way in which future research can move beyond the studies presented in this dissertation is through the integration of mixture models and person-specific analysis in prevention-related research. Rather than relying on post-hoc grouping (as was performed in study 2), models could be defined that examine unobserved groups of individuals for whom person-specific findings are similar. For example, given a larger sample size and more precise point estimates, researchers could replicate the findings from study 2 and perform latent profile analysis on the resulting person-specific parameters (i.e., “No Tanning” to “Tanning” transition probability, “Tanning” to “No Tanning” transition probability, log-linear estimate of the covariate effect). In this type of analysis, the heterogeneity in process and motivation across individuals would be accounted for through the use of the person-specific estimates, and sub-groups of tanners would be empirically derived using mixture models.

Study 1’s discussion of distal outcome bias highlighted another avenue for future research outside of what was detailed in its corresponding discussion section. Results of study 1 indicated that the bias in distal outcome recovery was related to model identification, such that the difference between true and estimated class means on the distal outcome was much larger when the model was not identified (i.e., 4 indicators – 3 classes) than when it was (i.e., 6 indicators – 3 classes). This information is useful, but does not sufficiently explore the issue of using the "classify-analyze" approach. Future research should seek to examine more completely the impacts of profile distinguishabilty and sample size on this approach to analyzing outcomes in latent class analysis. Results of the current study imply that the recovery of the true distal means will be poorer for models with less class separation (e.g., closer conditional probabilities) and less distinct classes (e.g., classes with conditional probabilities closer to .50). These findings are intuitive given that less distinguishable classes will likely result in greater misclassification, which, in turn, will obscure distal outcome differences across classes. It is also intuitive to assume that distal estimates in smaller samples will be more affected by this potential misclassification. Considering how desirable the ability to examine outcomes in mixture models is to substantive researchers, future work should seek to better quantify bias estimates and provide guidelines for situations where the "classify-analyze" paradigm might be appropriate. Moreover, the bias associated with this approach should be examined in other mixture models were distal outcomes are examined (e.g., latent profile analysis, growth mixture modeling) in order to provide more explicit recommendations for practice across methods.

Finally, one future area in prevention research that could benefit from the use of person-specific analysis is theory testing. For example, the often cited Theory of Planned Behavior (see study 3 for detail about the theory) was developed and tested in observational (Ajzen, 2002) and experimental research (e.g., Turrisi, Jaccard, Taki, Dunnam, & Grimes, 2001) on a sample of individuals at a single or small number of time points. As mentioned above, this theory posits that there are three proximal predictors of intentions to engage in a given behavior and that these intentions are the primary proximal predictor of behavior. This theory has been shown to be effective at accounting for inter-individual differences at the group-level, but it is likely that the proposed model would not hold for most participants if examined at the level of the individual over time. For example, at a daily level, it is possible that some individuals would only be motivated by daily perceived behavioral control (i.e., proximal predictor of intentions in the Theory of Planned Behavior), whereas others might not show concurrent or cross-lag relationships with any of the theoretical predictors. Using person-specific analysis, a reexamination of the theoretical models of influence on which prevention programs are based might provide researchers with new knowledge of how to best intervene across individuals.

<u>References - General Introduction and Conclusion</u>

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