TABLE 1
Demographic Variables by Stage of Change

Demographic Variables	Stage of Change: Precontemplation (n = 1,250)	Contemplation (n = 1,163)	Action (n = 772)	p Value[1]
Gender				.001
Female (n = 1,580)	30.1%	36.5%	33.4%	
Male (n = 1,605)	48.3%	36.5%	15.2%	
Skin Type				.001
High risk (n = 910)	29.1%	36.9%	34.0%	
Medium risk (n = 1,041)	40.2%	35.3%	24.6%	
Low risk (n = 1,234)	45.9%	37.3%	16.8%	
Condition				ns
Basic (n = 1,782)	38.7%	36.8%	24.6%	
Enhanced (n = 1,403)	40.0%	36.2%	23.8%	
Grade at Time of Post 2				ns
10th (n = 757)	40.8%	34.1%	25.1%	
11th (n = 2,428)	38.8%	37.3%	24.0%	

[1] Pearson χ^2 test of independence.

model that constrains the two effects to be the same (i.e. $\beta_1^{(1)} = \beta_1^{(2)}$) to a model that allows for differential effects. For this, the likelihood-ratio test (19) compares twice the difference in log-likelihood values of these two models to the χ^2 distribution. The degrees of freedom equal the number of additional parameters in the unconstrained model relative to the constrained model. Table 3 lists the results of the analyses with gender.

Comparing models yields a likelihood-ratio $\chi^2 = 6698.80 - 6690.24 = 8.56$ on 1 degree of freedom ($p < .005$) allowing us to reject the null hypothesis of a homogeneous gender effect on the two thresholds. As the results indicate, the gender effect is more pronounced on the action threshold ($\hat{\beta}_1^{(2)} = 1.029$) than on the contemplation threshold ($\hat{\beta}_1^{(1)} = .776$). Both gender effects are statistically significant ($p < .001$) by the so-called "Wald test" (20), which uses the ratio of the maximum likelihood parameter estimate to its standard error to determine statistical significance.[4] Both estimates are positive, indicating that females are more successful at crossing both thresholds relative to males (i.e. the thresholds are higher for males). Expressed as odds ratios yields exp (.776) = 2.17 and exp (1.029) = 2.80. Thus, females are a little more than twice as likely as males to be across the contemplation threshold and almost three times as likely as males to be across the action threshold.

To illustrate application of the model with more than a dichotomous explanatory variable, we focus on the effect of skin type. For this, two dummy-coded variables are used to contrast the three skin type levels: the first compares medium-risk to high-risk subjects, and the second dummy-code compares low-risk to high-risk subjects. Table 4 lists results for the Threshold of Change Model including skin type. The likelihood-ratio χ^2 equals = 6.72 on 2 degrees of freedom ($p < .05$), allowing us to reject the overall null hypothesis of equal effects. From the results allowing varying threshold effects, it is seen that for each skin type comparison the confidence intervals for the contemplation and action thresholds overlap. This suggests that the threshold effects are similar for a given skin type comparison. However, a more specific test of this hypothesis is obtained by examining whether the difference $\beta^{(2)} - \beta^{(1)}$ equals zero for each skin type comparison. The estimated difference in threshold effects equals $.455 - .490 = -.035$ (se = .102) for medium versus high risk and $.936 - .727 = .209$ (se = .105) for low versus high risk. Converting these to Wald statistics yields −.34 and 1.99, respectively, indicating a significant difference ($p < .05$) only for the low-versus high-risk contrast. Thus, comparing medium- to high-risk subjects indicates a similar effect on both thresholds, whereas comparing low- to high-risk subjects indicates a larger difference for the action threshold.

As all skin type estimates are highly significant ($p < .001$), there is considerable difference in the thresholds when comparing high-risk to medium- and low-risk subjects. Since these estimates are positively increasing, the thresholds are highest for low-risk subjects, intermediate for medium-risk subjects, and lowest for high-risk subjects. Expressed as odds ratios, high-risk subjects are 1.63 and 1.58 times as likely to be across the contemplation and action thresholds, relative to medium-risk subjects, and 2.07 and 2.55 times as likely to be across these same thresholds, relative to low-risk subjects.

Finally, we consider the general model including all demographic, attitude, and efficacy variables. Table 5 lists results considering both equal and varying threshold effects. Due to the large number of variables, instead of estimated effects, Table 5 lists the odds ratios that are calculated for each estimate (i.e. exp $\beta_h^{(j)}$ for the effect of variable h on the jth threshold). Odds ratios are listed for both assumptions of equal and varying effects. Significance of each odds ratio is indicated, as well as for the test of equal effect on the two thresholds.

In either model, gender has a significant effect, with males having significantly higher thresholds than females. However, as the varying effects model indicates, this difference is more pronounced for the action threshold than for the contemplation threshold. Females are 1.68 and 2.18 times as likely as males to be across the contemplation and action thresholds, respectively. These results for gender agree with the previous results in Table 3 that only considered the effect of gender on the thresholds. For skin type, similar to the previous bivariate results in Table 4, we see that the assumption of a homogeneous effect across thresholds is reasonable when comparing medium- to high-risk subjects, but is rejected when comparing low- to high-risk subjects. For the latter comparison, the difference is more pronounced for the action threshold, relative to the contemplation threshold. Notice that controlling for the other explanatory variables has reduced the magnitude of the odds ratios for skin type, as compared with the results in Table 4.

Turning to the attitude variables, positive attitudes about the sun is not significantly related to either threshold. For perceived susceptibility, there is a significant relationship, however there is no evidence of differential threshold effects. In terms of magnitude, those with the highest level of perceived susceptibility (i.e. definitely agree = 4) are estimated to be 2.46, 1.83, and 1.35 times as likely to be across both thresholds as subjects in categories 1, 2, and 3 of perceived susceptibility, respectively.

For worry about skin cancer and self-efficacy, in both cases, the assumption of equal effects on thresholds is rejected in favor of the model allowing differential effects. However, the direction is reversed for these two variables. For skin cancer worry, the effects are more pronounced in terms of the contemplation threshold, whereas for self-efficacy the effects are more pronounced in terms

[4] These test statistics (i.e. z = ratio of the parameter estimate to its standard error) are compared to a standard normal frequency table to test the null hypothesis that the parameter equals 0.

TABLE 2
Attitudes and Efficacy by Stage of Change

Variables	Precontemplation (n = 1,250)	Contemplation (n = 1,163)	Action (n = 772)	p Value[1]
	Stage of Change			
Positive Attitudes about the Sun				.001
Definitely disagree (n = 133)	53.4%	25.6%	21.1%	
Somewhat disagree (n = 1,241)	39.6%	35.5%	24.8%	
Somewhat agree (n = 1,537)	36.5%	39.1%	24.4%	
Definitely agree (n = 254)	46.9%	31.1%	22.0%	
Perceived Susceptibility to Sunburn				.001
Definitely disagree (n = 193)	67.4%	22.8%	9.8%	
Somewhat disagree (n = 1,226)	49.2%	34.5%	16.3%	
Somewhat agree (n = 1,325)	33.5%	41.1%	25.4%	
Definitely agree (n = 439)	16.4%	34.4%	49.2%	
Worried about Sunburn				.001
Definitely disagree (n = 32)	87.5%	6.3%	6.3%	
Somewhat disagree (n = 692)	57.2%	30.8%	12.0%	
Somewhat agree (n = 1,708)	41.3%	38.3%	20.3%	
Definitely agree (n = 753)	15.9%	38.9%	45.2%	
Efficacy to Protect Self from Sun				.001
Not at all confident (n = 340)	84.4%	13.8%	1.8%	
Slightly confident (n = 1,127)	51.3%	37.8%	10.9%	
Moderately confident (n = 1,308)	26.3%	45.2%	28.5%	
Very confident (n = 348)	8.6%	25.0%	66.4%	
Extremely confident (n = 62)	17.7%	19.4%	62.9%	

[1] Pearson χ^2 test of independence.

TABLE 3
Thresholds of Change Model: Gender Effect on Stage

Term	Parameter Estimates (95% Confidence Intervals): Equal Effect on Thresholds	Varying Effect on Thresholds
Intercept$^{(1)}$	−.904 (−1.004, −.804)	−.844 (−.952, −.736)
Gender$^{(1)}$	.870 (.737, 1.003)	.776 (.631, .921)
Intercept$^{(2)}$	.743 (.645, .841)	.689 (.585, .793)
Gender$^{(2)}$	—	1.029 (.857, 1.201)
−2 log L	6698.80	6690.24

$^{(1)}$ = effect on threshold 1 (contemplation threshold).
$^{(2)}$ = effect on threshold 2 (action threshold).
— = same effect as on threshold 1.

TABLE 4
Thresholds of Change Model: Skin Type Effect on Stage

Term	Parameter Estimates (95% Confidence Intervals): Equal Effect on Thresholds	Varying Effect on Thresholds
Intercept$^{(1)}$	−.922 (−1.049, −.795)	−.890 (−1.033, −.747)
Medium Risk$^{(1)}$	.487 (.324, .650)	.490 (.300, .680)
Low Risk$^{(1)}$	.801 (.640, .962)	.727 (.545, .909)
Intercept$^{(2)}$	.693 (.568, .818)	.665 (.528, .802)
Medium Risk$^{(2)}$	—	.455 (.259, .651)
Low Risk$^{(2)}$	—	.936 (.734, 1.138)
−2 log L	6772.73	6766.01

$^{(1)}$ = effect on threshold 1 (contemplation threshold).
$^{(2)}$ = effect on threshold 2 (action threshold).
— = same effect as on threshold 1.

of the action threshold. Individuals with the highest level of skin cancer worry (i.e. definitely agree = 4) are estimated to be 11.94, 3.28, and 2.21 times as likely to be across the contemplation threshold as individuals in the first three categories of this variable, respectively. However, for the action threshold, the same three estimated odds ratios are much lower, namely 2.31, 1.86, and 1.56. Thus, worry about skin cancer exerts a much greater effect on the contemplation threshold than the action threshold. Alternatively, for self-efficacy, odds ratio estimates indicate that individuals with the highest level (i.e. extremely confident = 5) are 73.37, 13.78, 4.73, and 1.08 times as likely to be across the action threshold and 18.41, 4.39, 1.67, and .59 times a likely to be across the contemplation threshold, as individuals with the four lower levels of self-efficacy, respectively. Thus, the effect of self-efficacy is much more pronounced in terms of the action threshold than the contemplation threshold. Interestingly, there is no statistical difference between the highest two levels of self-efficacy (i.e. very confident versus extremely confident) for either threshold. Also, for the contemplation threshold, there is no statistical difference between moderately confident and extremely confident individuals.

COMPUTER SOFTWARE

Although the statistical techniques for the Thresholds of Change Model are not new (6,7), statistical software for perform-

TABLE 5

Thresholds of Change Model—Odds Ratio (OR) Estimates Comparing Models Assuming Equal and Varying Effects on Thresholds

Term	Equal Effect OR	Varying Effects: Contemplation OR_1	Varying Effects: Action OR_2	p Value for $OR_1 = OR_2$
Grade (10 vs 9)	1.05	.99	1.17	ns
Gender (M vs F)	1.86***	1.68***	2.18***	.05
Condition	1.04	1.02	1.08	ns
Skin Type (compared to high risk)				
Medium risk	1.22*	1.26*	1.15	ns
Low risk	1.30*	1.15	1.67***	.05
Positive Attitudes about the Sun				
Category 1 vs 4	1.48	1.39	1.72	ns
Category 2 vs 4	.88	.84	1.00	ns
Category 3 vs 4	.82	.76	1.00	ns
Perceived Susceptibility				
Category 1 vs 4	2.46***	2.66***	1.95*	ns
Category 2 vs 4	1.83***	1.97***	1.58**	ns
Category 3 vs 4	1.35*	1.34	1.35*	ns
Worry about Skin Cancer				
Category 1 vs 4	8.24***	11.94***	2.31	.05
Category 2 vs 4	2.54***	3.28***	1.86***	.01
Category 3 vs 4	1.79***	2.21***	1.56***	.05
Self-Efficacy				
Category 1 vs 5	39.74***	18.41***	73.37***	.01
Category 2 vs 5	9.44***	4.39***	13.78***	.001
Category 3 vs 5	3.53***	1.67	4.73***	.001
Category 4 vs 5	.91	.59	1.08	ns

Notes: for test of OR = 1: *** $p < .001$ ** $p < .01$ * $p < .05$; higher odds ratios indicate higher thresholds.

ing such analysis is limited. SAS does include in its PROC LOGISTIC the ability to estimate the model assuming equal effects of the explanatory variables across thresholds; however, the more general model allowing for differential effects is not provided. SPSS does not include an ordinal regression procedure, so neither model (i.e. assuming equal or differential effects) is available. Of the more specialized software programs, the LIMDEP econometric software program (21) does allow estimation of the Thresholds of Change Model allowing for either equal or differential effects. Other software packages or programs that allow estimation of the model assuming equal effects include STATA, GAUSS, SUDAAN, and MIXOR.[5]

As an alternative, the programming facilities of the major statistical software packages (e.g. SPSS or SAS) can be used to develop tailor-made subprograms for estimation of the Thresholds of Change Model parameters. This is advantageous since such subprograms can directly interface with data sets from these packages. To this end, we have programmed an SPSS matrix subprogram that can estimate the Thresholds of Change Model assuming either equal or differential effects of the explanatory variables. This subprogram can be obtained from the first author (hedeker@uic.edu).

DISCUSSION

Although stage models, and notably the Stages of Change Model (1), are prominent in health behavior research, use of statistical techniques for distinguishing the ordinal levels of stage data or for evaluating the relative effect of explanatory variables in distinguishing stage membership has been limited. Perhaps one reason for this is that a common statistical technique for ordered response data, the Ordered Logistic Regression Model (also called the Proportional Odds Model [15,23]), assumes that explanatory variables have the same effect on all thresholds. While the Proportional Odds Model has been extended to allow for heterogeneous effects on the thresholds (6,7), use and formulation of this extended model for stages of change data has not previously been described. The Thresholds of Change Model addresses this gap in the literature and makes both a methodological and theoretical contribution to the field. From a theoretical perspective, this approach provides a means for statistically testing assumptions about explanatory variables and their relative influence on the stages of change.

A main feature of the Thresholds of Change Model is its focus on the thresholds that separate the ordered stages. Just as the stages are ordered, the thresholds are also ordered, each of increasing magnitude. In other words, the jump from precontemplation to contemplation is below that from contemplation into action. Thus, one can think of the thresholds as hurdles of increasing height. By estimating these thresholds, the probability of crossing each threshold can be determined for the population of subjects. Explanatory variables can exert their influence on these thresholds, and these effects can be assumed to be the same or to vary for each threshold. This latter feature is especially attractive in health behavior research since one can estimate the influence of an intervention (or other grouping of subjects) on each threshold separately.

[5] MIXOR (22) has been upgraded to allow for both equal and differential effects due to the explanatory variables. This updated version is available via the internet at http://www.uic.edu/~hedeker/mix.html. The results reported in this article were obtained using this program.

The Thresholds of Change Model offers several important contributions to health behavior change researchers. The procedure allows investigators to test two of the major assumptions underlying stage theories as outlined by Weinstein, Rothman, and Sutton (24): first, that some barriers to change are more important at certain stages than others, and second, that interventions that are stage-matched should be more effective than those that are mismatched to stage. As Weinstein et al. note, few, if any, prior studies have tested assumptions that different causal or explanatory factors are important at different stages. The Thresholds of Change Model provides a means for now conducting such investigations. Importantly, the Thresholds of Change Model can be used to help distinguish whether changes in specific health behaviors follow a stage or continuum process (c.f. Weinstein et al.).

The findings in the present paper also contribute to our understanding of what psychosocial and background variables are important for crossing each stage threshold, and specifically in this case, stages of change for sun protection. As expected, we found that our explanatory variables exerted differential effects on the different thresholds. Although self-efficacy was clearly an important variable at both thresholds (as evidenced by the magnitude of the odds ratios), it had a significantly greater effect on the action threshold than on the contemplation threshold. In contrast, worry about skin cancer had a greater effect on the contemplation threshold than on the action threshold, although it was still significant at the action threshold. Our "worry" scale could also be interpreted as a measure of the relative importance or seriousness of skin cancer to the youth at present. Perceived susceptibility exerted a similar effect on both thresholds, suggesting that feelings of being at risk are important not just for starting to think about taking precautions but also for actually doing so.

Gender differences also were relatively more important at the action than the contemplation threshold. Although both thresholds were higher for males than females, the gender difference was relatively greater at the action threshold, where females were more than twice as likely as males to be classified in action. These findings support the general notion of the Stages of Change Model that different processes are relatively more or less important for membership in the different stages, and the Thresholds of Changes Model provides an appropriate statistical method for testing this basic tenet. Our findings also have implications for tailoring interventions to stages of change. Clearly, increasing self-efficacy is critical for moving people from contemplation into action, far more so than increasing feelings of worry or the perceived relative importance of skin cancer. However, increasing feelings of concern and perceived importance of skin cancer to youth personally are important for moving precontemplators into contemplation.

One caution about our specific example and findings is worth noting. We divided participants into three stages—precontemplation, contemplation, and action—skipping over the stage of preparation and merging some adolescents who were in the maintenance stage with those in action. We were unable to construct a preparation stage because of the timing of our surveys and seasonal limitations of sun protection in the Chicago area. By definition, preparation requires some previous behavior change attempt in the past year and a more immediate plan to change behavior (within the next month). The seasonal nature of sun protection in the Chicago area and the relatively short summer season makes it practically impossible to have a separation between contemplation and preparation; it is meaningless to ask about a difference between intending to change behavior in the next 30 days versus the next 6 months when the 6 months time frame incorporates the winter months. Thus, although the separation between contemplation and action in other contexts might represent a two-stage jump (i.e. a preparation and and an action threshold), in the present study, it is only a one-stage jump (i.e. the action threshold). Also, our combining some youth who were in maintenance into the action stage may have affected the estimation of the action threshold, but given that less than 5% of the sample could be classified as in maintenance, they were unlikely to have much of an effect here.

Our Thresholds of Change Model is also applicable to studies that use a variety of designs. We have presented the model and all analyses for a cross-sectional design where there is a single observation per individual. This model has assumed that the responses from individuals are independent. Alternatively, designs where individuals are observed nested within clusters (i.e. schools, hospitals, clinics, firms) yield data where responses from individuals may not be independent but instead correlated within clusters. Another source of nonindependent response data occurs when stage data are obtained repeatedly across time from the same group of subjects. For statistical analysis of clustered and longitudinal data, mixed-effects models have become increasingly used (25–28). In this regard, we have developed a mixed-effects ordinal regression model (29) that can be used to estimate a clustered or longitudinal Thresholds of Change Model assuming equal explanatory variable effects on the thresholds. A further development of the Thresholds of Change Model for clustered or longitudinal stage data that allows for differential effects is described in Hedeker and Mermelstein (10). Hopefully, the development of TCM described in this paper and its extensions will provide researchers with useful methods for analyzing stages of change data.

APPENDIX A

Statistical Development of TCM

If a standard logistic distribution is assumed for the latent readiness of change variable in the population, the probability for a given subject i ($i = 1, \ldots, N$) that $Y_i = j$ (a response for subject i occurs in category j on stage variable Y) is given by:

$$P(Y_i = j) = \Psi[\beta_0^{(j)} + \mathbf{x}_i'\boldsymbol{\beta}^{(j)}] - \Psi[\beta_0^{(j-1)} + \mathbf{x}_i'\boldsymbol{\beta}^{(j-1)}] \qquad (7)$$

where the logistic response function (the cumulative distribution function of the standard logistic distribution) is $\Psi\ [\beta_0^{(j)} + \mathbf{x}_i'\ \boldsymbol{\beta}^{(j)}] = 1/(1 + \exp\{-[\beta_0^{(j)} + \mathbf{x}_i'\boldsymbol{\beta}^{(j)}]\})$, and $\mathbf{x}_i$ is the vector of explanatory variables for subject i. The model can also be expressed in terms of $J - 1$ cumulative logits, namely,

$$\log\left[\frac{P(Y \leq j)}{1 - P(Y \leq j)}\right] = \beta_0^{(j)} + \mathbf{x}_i'\boldsymbol{\beta}^{(j)}, \qquad j = 1, \ldots, J-1, \quad (8)$$

which can be seen as a generalization of the (binary) logistic regression model for ordinal responses, that is, an ordinal logistic regression model.

If the regression coefficients are all assumed to be equal across the $J - 1$ cumulative logits (i.e. $\boldsymbol{\beta}^{(1)} = \boldsymbol{\beta}^{(2)} = \ldots \boldsymbol{\beta}^{(J-1)}$) the model is termed the proportional odds model, as described by McCullagh (23). In this case, the $\boldsymbol{\beta}$ parameters do not carry the j superscript in equation (8).

Allowing for some of the explanatory variables to have differential effects on the cumulative logits, and some to have the same effect, results in the partial proportional odds model proposed by Peterson and Harrell (6). This model can be written as

$$\log\left[\frac{P(Y\leq j)}{1-P(Y\leq j)}\right] = \beta_0^{(j)} + \boldsymbol{x}'_i\boldsymbol{\beta}^{(j)} + \boldsymbol{w}'_i\boldsymbol{\alpha}, \quad j=1,\ldots,J-1, \quad (9)$$

where $\boldsymbol{x}_i$ and $\boldsymbol{w}_i$ are vectors containing the explanatory variables with differential and equal effects, respectively.

In many presentations of the ordinal logistic regression model, it is only the parameters $\beta_0^{(j)}$ in equation (9) that are referred to as the thresholds or cutpoints. With this view in mind, equation (9) could be written as:

$$\log\left[\frac{P(Y\leq j)}{1-P(Y\leq j)}\right] = \beta_{0i}^{(j)} + \boldsymbol{w}'_i\boldsymbol{\alpha} \quad (10)$$

with

$$\beta_{0i}^{(j)} = \beta_0^{(j)} + \boldsymbol{x}'_i\boldsymbol{\beta}^{(j)}. \quad (11)$$

In this specification, the "thresholds" $\beta_{0i}^{(j)}$ depend on explanatory variables $\boldsymbol{x}_i$, while the variables $\boldsymbol{w}_i$ have the same effect on all cumulative logits, and thus across all thresholds. Following this specification, equation (11) could be designated as the Thresholds of Change Model. In this article, we have simplified the presentation by denoting γ_j as the thresholds and $\gamma_j = \beta_0^{(j)} + \boldsymbol{x}'_i\boldsymbol{\beta}^{(j)} + \boldsymbol{w}'_i\boldsymbol{\alpha}$ as the Thresholds of Change Model (i.e. the right side of equation [9]). Either representation results in the same statistical model (i.e. a partial proportional odds model), however we feel it is simpler to denote the Thresholds of Change Model as $\gamma_j = \beta_0^{(j)} + \boldsymbol{x}'_i\boldsymbol{\beta}^{(j)} + \boldsymbol{w}'_i\boldsymbol{\alpha}$ and to note that the covariates $\boldsymbol{w}$ have homogeneous effects on the thresholds.

As an alternative to the logistic distribution, the standard normal distribution can be assumed for the latent readiness of change variable in the population. In this case, $\Phi(\cdot)$, the cumulative standard normal distribution function, replaces the logistic function $\Psi(\cdot)$ in the development given above. The model assuming equal regression coefficients results in the ordinal probit regression model described in McKelvey and Zavoina (8), while the generalization allowing for differential effects is described by Terza (7). For either the probit or logistic model, maximum likelihood techniques can be used for parameter estimation; details can be found in Bock (4) or Agresti (15).

REFERENCES

(1) Prochaska JO, DiClemente C: Stages and processes of self-change in smoking: Toward an integrative model of change. *Journal of Consulting and Clinical Psychology.* 1983, *51:*390–395.

(2) Prochaska JO, DiClemente C, Norcross J: In search of how people change: Applications to addictive behaviors. *American Psychologist.* 1992, *47:*1102–1114.

(3) Flay B: Youth tobacco use: Risks, patterns, and control. In Slade J, Orleans CT (eds), *Nicotine Addiction: Principles and Management.* New York: Oxford Press, 1993.

(4) Bock RD: *Multivariate Statistical Methods in Behavioral Research.* New York: McGraw-Hill, 1975.

(5) Long JS: *Regression Models for Categorical and Limited Dependent Variables.* Thousand Oaks, CA: Sage Publications, 1997.

(6) Peterson B, Harrell FE: Partial proportional odds models for ordinal response variables. *Applied Statistics.* 1990, *39:*205–217.

(7) Terza J: Ordinal probit: A generalization. *Communications in Statistics.* 1985, *14:*1–12.

(8) McKelvey RD, Zavoina W: A statistical model for the analysis of ordinal level dependent variables. *Journal of Mathematical Sociology.* 1975, *4:*103–120.

(9) Winship C, Mare RD: Regression models with ordinal variables. *American Sociological Review.* 1984, *49:*512–525.

(10) Hedeker D, Mermelstein RJ: A multilevel thresholds of change model for analysis of stages of change data. *Multivariate Behavioral Research.* 1998, *33:*427–455.

(11) Collins LM, Wugalter SE: Latent class models for stage-sequential dynamic latent variables. *Multivariate Behavioral Research.* 1992, *27:*131–137.

(12) Martin RA, Velicer WF, Fava JL: Latent transition analysis applied to the stages of change for smoking cessation. *Addictive Behaviors.* 1996, *21:*67–80.

(13) Velicer WF, Martin RA, Collins LM: Latent transition analysis for longitudinal data. *Addiction.* 1996, *91*(Suppl.):S197–S209.

(14) Collins LM, Wugalter SE, Rousculp SS: *LTA User's Manual.* Los Angeles: J. P. Guilford Laboratory of Quantitative Psychology, University of Southern California, 1991.

(15) Agresti A: *Categorical Data Analysis.* New York: Wiley, 1990.

(16) Little RJA: Modeling the drop-out mechanism in repeated-measures studies. *Journal of the American Statistical Association.* 1995, *90:*1112–1121.

(17) Hedeker D, Gibbons RD: Application of random-effects pattern-mixture models for missing data in longitudinal studies. *Psychological Methods.* 1997, *2:*64–78.

(18) Fitzpatrick TB: Soleil et peau. *Journal of Medical Esthetics.* 1975, *2:*33–34.

(19) Silvey SD: *Statistical Inference.* New York: Chapman and Hall, 1975.

(20) Wald A: Tests of statistical hypotheses concerning several parameters when the number of observations is large. *Transactions of the American Mathematical Society.* 1943, *54:*426–482.

(21) Greene WH: *LIMDEP Version 7.0 User's Manual.* Bellport, NY: Econometric Software, Inc., 1995.

(22) Hedeker D, Gibbons RD: MIXOR: A computer program for mixed-effects ordinal regression analysis. *Computer Methods and Programs in Biomedicine.* 1996, *49:*157–176.

(23) McCullagh P: Regression models for ordinal data (with discussion). *Journal of the Royal Statistical Society, Series B.* 1980, *42:*109–142.

(24) Weinstein ND, Rothman AJ, Sutton SR: Stages theories of health behavior: Conceptual and methodological issues. *Health Psychology.* 1998, *17:*290–299.

(25) Bryk AS, Raudenbush SW: *Hierarchical Linear Models: Applications and Data Analysis Methods.* Newbury Park, CA: Sage Publications, Inc., 1992.

(26) Goldstein H: *Multilevel Statistical Models* (2nd Ed.). New York: Halstead Press, 1995.

(27) Hedeker D, Gibbons RD, Flay BR: Random-effects regression models for clustered data with an example from smoking prevention research. *Journal of Consulting and Clinical Psychology.* 1994, *62:*757–765.

(28) Hedeker D, Mermelstein RJ: Application of random-effects regression models in relapse research. *Addiction.* 1996, *91*(Suppl.):S211–S229.

(29) Hedeker D, Gibbons RD: A random-effects ordinal regression model for multilevel analysis. *Biometrics.* 1994, *50:*933–944.