THE THRESHOLDS OF CHANGE MODEL: AN APPROACH TO ANALYZING STAGES OF CHANGE DATA[1,2,3]

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ABSTRACT

Stage models are prominent in research describing health behavior change. Since stage models often propose that different factors have varying influences on membership in the different stages, statistical methods that can estimate the thresholds that separate the stages and the relative value of variables in influencing these thresholds are useful. This article describes use of a "thresholds of change" model for analyzing the thresholds separating stages and specifically for examining the effects of explanatory variables on these thresholds using a generalization of an ordinal logistic (or probit) regression model. Data from a skin cancer prevention study (N = 3,185) in which participants were grouped into three stages for sunscreen use (precontemplation, contemplation, and action) are used to illustrate the Thresholds of Change Model. For this example, two thresholds exist: a contemplation (between precontemplation and contemplation) and an action threshold (between contemplation and action). Variables examined include gender, skin type, perceived susceptibility to sunburn, worry about skin cancer, and sun protection self-efficacy. We examine models that assume that the effects of these variables are the same across thresholds, and then allow the effects of these variables to vary across thresholds. Results indicate that perceived susceptibility has an equal effect on both thresholds, but that worry and self-efficacy have differential effects: worry exerts a greater influence on the contemplation threshold, whereas self-efficacy has a significantly stronger effect on the action threshold. Gender also has a stronger effect on the action threshold; males were less likely to be classified in the action stage than females. This analytic approach has broad applications to many types of stage data.

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INTRODUCTION

Stage models are prominent in research describing health behavior change. Among the most notable models is the Transtheoretical Model of Change (or Stages of Change Model) (1,2). This model proposes that behavior change involves a progression through five stages of change: precontemplation, contemplation, preparation, action, and maintenance, all of which vary along a continuum of readiness to change. Stage models are also common in the adoption of problem behaviors. Flay (3) describes five stages of smoking initiation among children and adolescents: preparation, trying, experimental use, regular use, and addiction. Stage models often propose that different factors characterize each stage and have varying influences on membership across the different stages. For example, the Stages of Change Model suggests that motivational processes such as consciousness-raising might be more important in distinguishing the precontemplation from the contemplation stage, but that other processes, such as self-reevaluation or self-liberation, might be more important in distinguishing contemplation versus preparation or action (2). Similarly, in the adoption of smoking, peer influence might be more important in separating the early stages, while mood management or physiological feedback may be more important as adolescents progress from experimental use to regular use and addiction.

In this article, we propose and describe use of the Thresholds of Change Model (TCM) for analysis of stages of change data. The term "threshold" is used as defined in the statistical literature (e.g., see Bock (4) page 513, or Long (5) page 116); namely, each threshold indicates the probability of membership below a given stage category versus the probability of membership at or above the same stage category. TCM focuses on estimation of these thresholds that separate the stages of change categories, as well as assessing the influence of variables (e.g. intervention group, mediating attitudes) on these thresholds. The influence of explanatory variables can be constrained to be the same on all thresholds or allowed to vary by threshold. The latter option is important in health behavior change research in order to examine, for example, whether interventions that are not successful in increasing the proportion of individuals in the action stage are nonetheless successful in moving individuals into the contemplation stage. The parameters of the Thresholds of Change Model are estimated using an extension of the ordinal logistic regression model described by Peterson and Harrell (6) or an extension of the ordinal probit regression model described by Terza (7). Thus, while the statistical techniques for the Thresholds of Change Model are not new, their application and development specific to stages of change data are.

As there are more readily available methods for measurement data (e.g. analyses of variance [ANOVA] or linear regression), it is important to note advantages of using the proposed TCM rather than simply analyzing ordinal responses as measurements using more traditional methods. One advantage is that the probit or logistic specifications of the TCM take into account the ceiling and floor effects of the dependent variable, whereas linear models for measurement data clearly do not. Thus, an ordinary linear regression model could yield predicted stage values below or above the admissable range (i.e. less than the minimum stage value or greater than the maximum stage value). As McKelvey and Zavoina (8) point out, due to the ceiling and floor effects of the dependent

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variable, values of the residuals and regressors will be correlated when linear models for measurement data are applied to ordinal outcomes, which can result in biased estimates of the regression coefficients. Furthermore, as Winship and Mare (9) note, the advantage of ordinal regression models (like the TCM) in accounting for ceiling and floor effects of the dependent variable is most critical when the dependent variable is highly skewed, or when groups, defined by different covariate values, are compared which have widely varying skewness in the dependent variable. Finally, unlike the proposed TCM, linear models for measurement data cannot detect a bidirectional effect, for example, if an intervention simultaneously increases responses in the highest and lowest stages.

The model presented here is for cross-sectional stage data. An extension of TCM for longitudinal data is proposed in Hedeker and Mermelstein (10). An alternative approach for longitudinal stage data, termed latent transition analysis (LTA), defines the stages of change as a dynamic latent variable (11–13). A software program for LTA is described by Collins, Wugalter, and Rousculp (14). Hedeker and Mermelstein (10) list some of the differences between LTA and TCM for longitudinal stage data. In practical terms, LTA allows a more complete view of the transitions between particular stages, although it is more limited than TCM in the number of explanatory variables that can be accomodated. Thus, while the two methods are complementary, TCM is more focused on assessing predictors of the stages while LTA focuses more on examining transitions between the stages.

To illustrate TCM, data are presented from a skin cancer prevention intervention among adolescents. Study participants were grouped into three stages of readiness for sunscreen use: precontemplation, contemplation, and action. For these three stages there are two thresholds: one between precontemplation and contemplation (contemplation threshold) and another between contemplation and action (action threshold). We considered three types of variables and their influence on stage: background factors (e.g. risk level and demographics), intervention condition, and attitudes. We hypothesized differential effects of attitudinal variables on the two thresholds. Specifically, we hypothesized that the motivational, attitudinal variables of "perceived susceptibility" and "worry about skin cancer" would exert a greater effect on the contemplation threshold than on the action threshold, but that "self-efficacy for sun protection" would show the opposite pattern, having a stronger influence on the action threshold. We also proposed that "positive attitudes about the sun," a possible barrier to protection, would show equal effects on the two thresholds. In terms of background variables, we expected that skin type, an indicator of risk level for skin cancer, would exert its primary effect on the action threshold. We also hypothesized that our intervention condition differences would show equal effects at both thresholds.

THRESHOLDS OF CHANGE MODEL (TCM)

To introduce and motivate application of TCM, we utilize the "threshold concept" (4), which posits that a continuous distribution of readiness of change exists in the population. This readiness of change variable is not directly observed; instead, individuals are classified into stages of change depending on their assumed value on the continuous latent readiness of change variable. For J ordered stages of change categories, $J - 1$ thresholds (denoted $\gamma_1 \cdots \gamma_{J-1}$) separate individuals into the stages. For example, if individuals are classified into stages of precontemplation, contemplation, or action (i.e. $J = 3$), then two thresholds exist: a contemplation threshold (γ_1 between the precontemplation and contemplation stages) and an action threshold (γ_2 between the contemplation and action stages).

These thresholds can be conceptualized as hurdles of increasing difficulty that separate individuals into the (increasing) stages of change. Estimation of these thresholds provides summary information that can be used to characterize a population of individuals in terms of the stages of change. In particular, estimation of the thresholds for different groups of individuals allows direct comparison of the groups in their stages of change data. For example, one might be interested in examining whether the contemplation and action thresholds are at the same level for males and females or between treatment and control groups.

To estimate these thresholds, a distribution must be assumed for the underlying latent readiness of change variable. Convenient choices for this distribution are the normal and logistic distributions, leading, respectively, to ordinal probit and logistic regression models (4,15). Figure 1a illustrates the cumulative distribution function for a logistic distribution of the latent readiness of change variable. Also indicated in Figure 1a are contemplation and action thresholds separating three stages of change categories.

As depicted, the thresholds are on the same scale as the latent readiness of change variable, while the y-axis indicates the response probabilities for the stages. These probabilities are obtained by the logistic response function, namely $p = 1/(1 + \exp(-\gamma))$ for a given threshold value γ. Each threshold value indicates the probability of a response below a given stage category (p) versus the probability of a response in or above the same stage category ($1 - p$). As shown in Figure 1a, the contemplation threshold value of -1 yields .27 as the probability of a response below contemplation (i.e. in precontemplation) and .73 as the probability of a response at or above contemplation (i.e. in contemplation or action). Similarly, for the action threshold of 1, the probability of a response below action (i.e. in precontemplation or contemplation) equals .73, while the probability of a response in action equals .27. The probability of a response in the contemplation category is the difference in probabilities associated with these two thresholds (i.e. contemplation equals $.73 - .27 = .46$).

The statistical development of TCM is included in Appendix A. Here, we focus on model definition and interpretation. Consider the following TCM (assuming three stages) to assess the influence of explanatory variables on the thresholds:

$$\gamma_1 = \beta_0^{(1)} + \boldsymbol{x}'\boldsymbol{\beta}^{(1)} \tag{1}$$

$$\gamma_2 = \beta_0^{(2)} + \boldsymbol{x}'\boldsymbol{\beta}^{(2)} \tag{2}$$

where $\boldsymbol{x}$ is a set of explanatory variables that are thought to be related to either or both of the thresholds. If $\beta^{(1)} < 0$ and $\beta^{(2)} < 0$ for a particular explanatory variable, then the variable lowers both thresholds and so has a benefical effect on both (assuming that the behavior under study is beneficial). Alternatively, if $\beta^{(1)} > 0$ and $\beta^{(2)} > 0$, then the variable elevates both thresholds and has a hazardous effect. If both $\beta^{(1)} = 0$ and $\beta^{(2)} = 0$, then the variable has no effect on the thresholds, and thus no effect on stage of change membership. More generally, a variable can have effects of different magnitude or sign on the $J - 1$ thresholds.

Allowing variables to have differential effects on the thresholds is clearly a tenet of the stages of change theory, since it is theorized that some variables are able to distinguish individuals in precontemplation versus contemplation (i.e. influence the contemplation threshold γ_1), but have little effect on action (i.e. have no effect on the action threshold γ_2). Similarly, other variables like

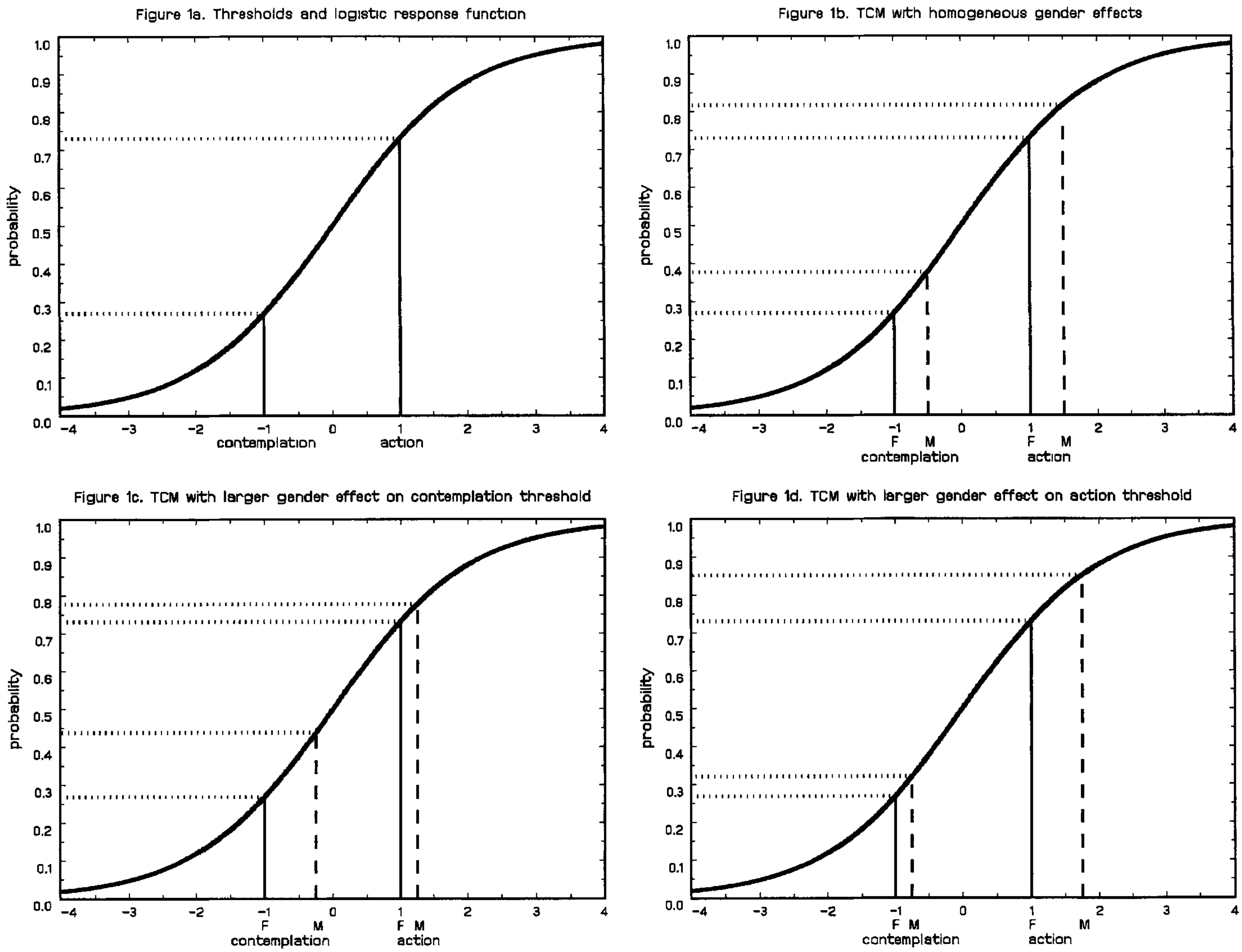

FIGURE 1: Logistic distribution and TCM.

self-efficacy, for example, might be better able to distinguish individuals in action versus those below action (i.e. influence the action threshold γ_2) than in distinguishing those above and below the contemplation threshold. Allowing for differential effects on the thresholds thus permits researchers to clearly determine the effect of explanatory variables in distinguishing between all cuts of the ordinal stages of change outcome.

As an example, consider the following TCM (assuming three stages) with gender as the only explanatory variable:

$$\gamma_1 = \beta_0^{(1)} + \beta_1^{(1)}x \tag{3}$$

$$\gamma_2 = \beta_0^{(2)} + \beta_1^{(2)}x \tag{4}$$

where x is an indicator variable (e.g. $x = 0$ for females and $x = 1$ for males). As depicted in Figure 1b, the thresholds equal -1 and 1 for females (i.e. $\beta_0^{(1)} = -1$ and $\beta_0^{(2)} = 1$) and $-.5$ and 1.5 for males (i.e. $\beta_1^{(1)} = \beta_1^{(2)} = .5$). As can be seen, the effect of gender on both thresholds is the same; the male thresholds are .5 greater than the female thresholds, indicating that males have a lower probability of crossing both thresholds. The odds ratio (OR) comparing males to females is also the same for both thresholds ($\exp \beta_1^{(1)} = \exp \beta_1^{(2)} = \exp .5 = 1.65$), indicating that the odds of a response in the stage categories below each threshold are 1.65 times as likely for males compared to females.

Figures 1c and 1d depict the same model allowing for differential threshold effects. In Figure 1c, the gender effect is more pronounced in terms of contemplation than action (i.e. $\beta_1^{(1)} = .75$ and $\beta_1^{(2)} = .25$). Here, the probability of action is reasonably similar for females and males (OR = 1.28); however, the probability of crossing the contemplation threshold is much greater for females than males (OR = 2.12). Conversely, Figure 1d illustrates a greater gender effect on the action threshold than on the contemplation threshold (i.e. $\beta_1^{(1)} = .25$ and $\beta_1^{(2)} = .75$). For Figure 1d, males and females are more similar in terms of crossing the contemplation threshold (OR = 1.28) than in crossing the action threshold (OR = 2.12).

In allowing for differential threshold effects, one caveat needs to be mentioned. By definition, the action threshold cannot be less than the contemplation threshold ($\gamma_2 > \gamma_1$, or more generally, $\gamma_j > \gamma_{j-1}$). For a continuous explanatory variable x, unless $\beta^{(1)}$ is set equal to $\beta^{(2)}$, inevitably $\gamma_2 < \gamma_1$ for some values of x. Essentially, allowing $\beta^{(1)} \neq \beta^{(2)}$ results in nonparallel regression lines (for the $J - 1$ regressions of the logit of p on x; see Appendix

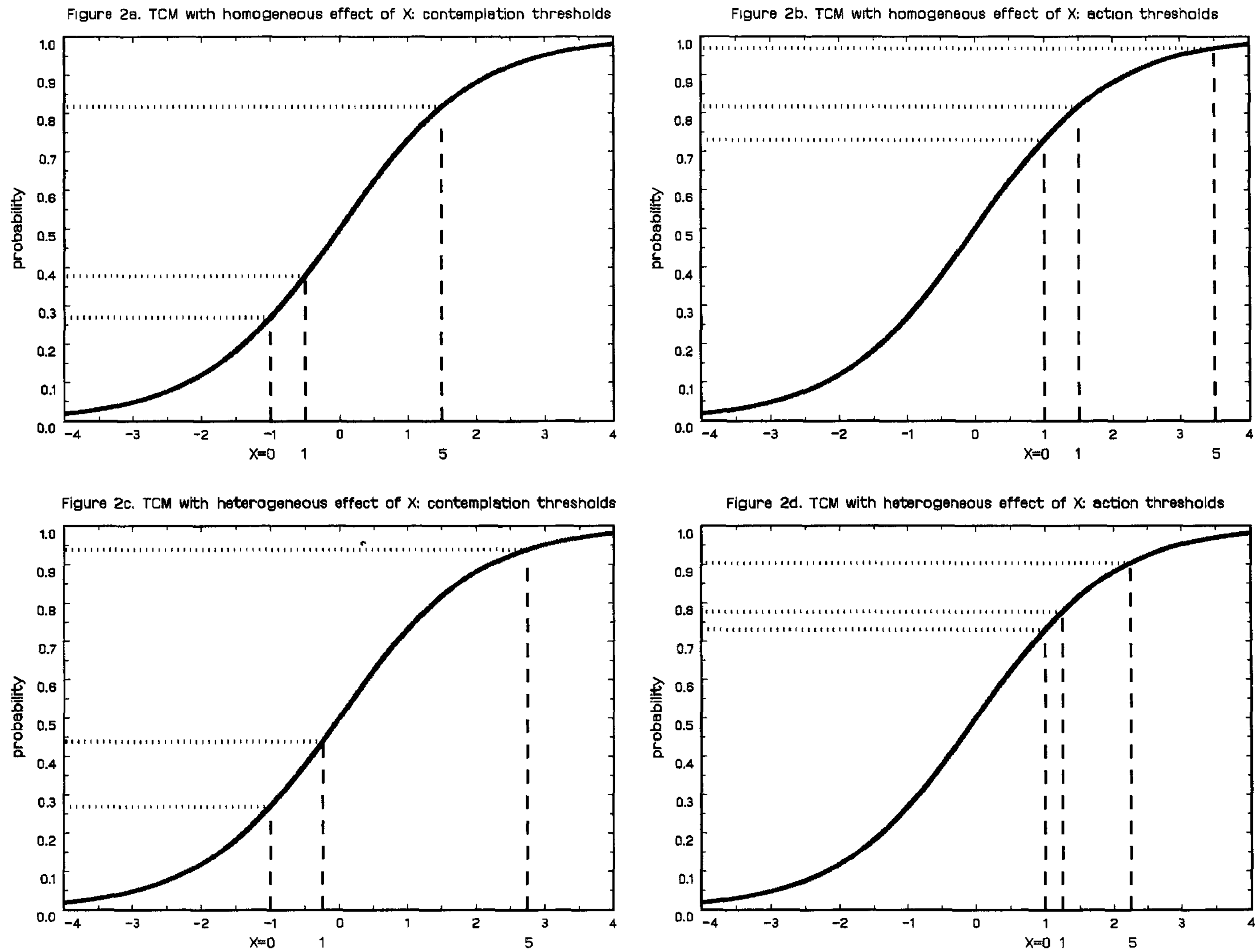

FIGURE 2: TCM for a continuous explanatory variable.

A), which cross at some point. Figures 2a–d illustrate this situation. In Figures 2a and 2b, the effect of x is assumed to be the same on both contemplation and action thresholds, and so the action threshold (Figure 2b) exceeds the contemplation threshold (Figure 2a) for every value of x. Alternatively, Figures 2c and 2d illustrate a greater effect of x on the contemplation threshold than on the action threshold. Notice that for $x = 5$ the action threshold is less than the contemplation threshold, yielding the untenable result that the probability of an action response (from Figure 2d, $p = .10$ for $x = 5$) is greater than the probability of either an action or contemplation response (from Figure 2c, $p = .06$ for $x = 5$).

Permitting differential threshold effects does not lead to the same problem with categorical explanatory variables. For a categorical variable with K levels, including $K - 1$ contrasts for each of the $J - 1$ thresholds leads to a saturated model for that two-way table (i.e. explanatory variable by stage variable), fitting the observed marginal proportions of that two-way table exactly. In this case, the crossing of the nonparallel regression lines occurs outside of the data range (i.e. for values either greater than or less than the actual values of the categorical variable or contrast). Thus, to allow for differential threshold effects, it is advantageous to categorize continuous explanatory variables.

In sum, the purpose of this paper is to present the Thresholds of Change Model, which is an approach for analyzing cross-sectional stages of change data. This model can be used to test the relative effects of mediating or explanatory variables on stage membership, including estimation of the magnitude of the thresholds between stages. As noted, for a categorical explanatory variable with K categories, one should use $K - 1$ contrasts to allow for heterogeneous threshold effects. For a continuous explanatory variable, one should either specify homogeneous threshold effects or, if possible, categorize the continuous variable to allow for heterogeneous threshold effects.

METHOD

Overview of Dataset and Variables

To illustrate application of TCM, data are used from a school-based skin cancer prevention program designed to reduce skin cancer-related risk behaviors and to increase sun protective behaviors among high school students. The project was conducted in 10 suburban high schools in the Chicago area. The 10 schools were randomly assigned to either a Basic ($n = 1{,}782$) or Enhanced ($n = 1{,}403$) treatment condition. The primary intervention ("Eclipse" project) took place during the 1994–1995 academic year. Students in the Basic condition received a one-class session covering skin cancer risk factors and protection. Students in the Enhanced condition received the same information as those in the Basic condition, but in addition, they received a personalized risk assessment along with newsletters during the summer of 1995 to help promote sun protection. Data were collected at four timepoints: baseline (fall 1994) and three follow-ups (Post 1, spring 1995; Post 2, fall 1995; and Post 3, fall 1996). All data reported in this paper are from the Post 2 data collection. This timepoint was chosen to assess stage of change for the first summer following the intervention. At all timepoints, students completed a questionnaire that contained a consistent core of questions: (a) demographics and measures of predisposing risk factors (e.g. race, gender, skin type, hair color); (b) knowledge about skin cancer, risk factors, and protection; (c) past and current sun exposure and protection behaviors; (d) future intentions about sun exposure and protection; and (e) related attitudes and self-efficacy for protection.

Participants

Participants were 3,185 (49.6% female) high school students who completed the Post 2 follow-up survey. Of 3,920 students who completed a baseline survey, 2,809 (71.7%) were included in this paper; the additional 376 students were measured at Post 2 but not at baseline. At the time of the survey, 76.2% were in the 11th grade, and the average age was 16.3 years. Ethnic representation was 78.7% White, 10.2% Asian/Pacific Islander, 7.7% Hispanic, 1.0% African–American, and 2.4% Other. This ethnic breakdown was in close agreement with the ethnic breakdown reported by the schools, which were chosen to provide students who were at risk for skin cancer.

The sample used in the present illustration—students with complete data at Post 2—is not the complete set of students from the study. As such, the analyses presented could suffer from selection biases to the degree that the sample of students used in the analyses is not representative of the original larger sample of students. However, students with complete versus incomplete data at Post 2 did not differ significantly on baseline measurements of the variables of interest in this paper. Thus, there is reasonable evidence that the analyses reported in this paper are not biased due to selection. Further methods for dealing with missing longitudinal data are described in Little (16) and Hedeker and Gibbons (17).

Measures

Skin type was assessed with a modification of Fitzpatrick's (18) skin types, describing how one's skin reacts to the sun upon initial exposure to the summer sun, without sunscreen, for 1 hour at midday. Participants who responded "always burn, unable to tan" or "usually burn, then can tan if I work at it" (Types I and II) were considered high risk; "sometimes mild burn, then tan easily" (Type III) were considered medium risk; and "rarely burn, tan easily" (Type IV) were considered low risk.

Perceived susceptibility was assessed with a 6-item scale to which participants responded using a 4-point Likert scale ranging from "definitely disagree" to "definitely agree." Coefficient alpha for this scale was .80. Examples of items of this scale included, "I'm at risk for sunburns" and "I'm at risk for getting skin cancer."

Worry about skin cancer was measured with a 4-item scale whose coefficient alpha was .60. Participants rated their level of agreement with each item using a 4-point Likert scale. Items on this scale included, "I don't need to worry about skin cancer until I'm much older" and "It's not worth worrying about skin cancer."

Positive attitudes about the sun was a 12-item scale asking respondents to agree or disagree with statements such as "Being in the sun improves my mood" and "I feel better with a tan." Participants rated their level of agreement with each statement on the same 4-point Likert scale as with the other attitude scales. Coefficient alpha for this scale was .88.

Self-efficacy for sun protection was assessed with an 11-item scale asking participants to rate how confident they felt doing a variety of sun protective behaviors in different situations. Participants responded to each item using a 5-point Likert scale ranging from "not at all confident" to "extremely confident." Coefficient alpha was .88.

Stage of change for sunscreen use was measured using a combination of items asking about frequency of sunscreen use and whether they intended to protect themselves consistently in the future. Participants were classified as: (a) precontemplators—those who were not currently regularly using sunscreen (frequency of never, rarely, or sometimes) and who did not intend to do so in the future; (b) contemplators—those who also were not currently regularly using sunscreen, but who did plan to do so in the future; or (c) action participants—those who were currently regularly using sunscreen (frequency of either often or always) regardless of whether they were considering increasing their future use.

Variable Coding

Dummy-coded variables were constructed for all explanatory variables. School grade, gender, skin type and condition were coded as follows: (a) grade at baseline (0 = 9th, 1 = 10th); (b) gender (0 = female, 1 = male); (c) skin type (dummy 1: high risk = 0 versus medium risk = 1, and dummy 2: high risk = 0 versus low risk = 1); and (d) condition (0 = basic, 1 = enhanced). For sun-related attitudes and efficacy, the multiple item index scores were rounded to the nearest integer, then a series a dummy codes were created, in each case using the highest category as the reference group. For the sun-related attitudes, three dummy variables were created to represent each scale (1 versus 4, 2 versus 4, 3 versus 4); for efficacy, four dummy variables were created (1 versus 5, 2 versus 5, 3 versus 5, 4 versus 5).

TCM RESULTS

Table 1 displays the bivariate relationships between stage of change and the demographic predictors, while Table 2 displays the relationships between stage of change and the attitudes and efficacy variables.

Performing χ^2 tests of independence yields statistically significant results ($p < .001$) for all variables except condition and grade (both with $p > .1$). These tests indicate that each variable (except condition and grade) is associated with stage in a bivariate manner. They do not reveal anything about the influence of these variables on membership in particular stage categories or allow estimation of effects controlling for other explanatory variables. As will be shown, TCM can be used to address these issues.

We first illustrate application of TCM for a dichotomous explanatory variable. Consider the following model for the contemplation and action thresholds (γ_1 and γ_2):

$$\gamma_1 = \beta_0^{(1)} + \beta_1^{(1)} Gender \tag{5}$$

$$\gamma_2 = \beta_0^{(2)} + \beta_1^{(2)} Gender \tag{6}$$

where *Gender* is coded as 0 for females and 1 for males. The null hypothesis of homogeneous effects can be tested by comparing a

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	Stage of Change: Precontemplation (n = 1,250)	Contemplation (n = 1,163)	Action (n = 772)	p Value[1]
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	−.844
	(−1.004, −.804)	(−.952, −.736)
Gender$^{(1)}$	.870	.776
	(.737, 1.003)	(.631, .921)
Intercept$^{(2)}$	.743	.689
	(.645, .841)	(.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	−.890
	(−1.049, −.795)	(−1.033, −.747)
Medium Risk$^{(1)}$	.487	.490
	(.324, .650)	(.300, .680)
Low Risk$^{(1)}$	.801	.727
	(.640, .962)	(.545, .909)
Intercept$^{(2)}$	.693	.665
	(.568, .818)	(.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:

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

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

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

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).

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