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An Application of the Thresholds of Change Model to the Analysis of Mental Health Data

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The threshold of change model (TCM) is a statistical technique for analyzing ordered stages of change variables. TCM focuses on the thresholds that separate the ordered stages, and the effects of explanatory variables are evaluated in terms of raising or lowering the thresholds. TCM also allows the explanatory variables to exert differential influence on each threshold. In this paper, we use TCM to analyze the data from a clinical trial that compared assertive community treatment (ACT) with standard case management (SCM) for patients with co-occurring severe mental illness and substance use disorder. Endpoint data (36-month follow up) were used for this analysis. The response variable is the recoded Substance Abuse Treatment Scale with three ordered levels (engagement/persuasion, active treatment, and recovery/relapse prevention), and hence two thresholds. The explanatory variables are gender and group (ACT vs. SCM). The results indicate that gender exerts constant and significant effects on both thresholds. The group effect is somewhat mixed: ACT lowers the first threshold (active treatment), but raises the second threshold (recovery/relapse prevention).

KEY WORDS: threshold of change; ordinal data; proportional odds; cumulative logit; assertive community treatment.

Treatment for many mental illnesses is a progressive process, which usually takes several stages from early treatment to recovery. For example, treatment for substance abuse among persons with severe mental illness involves at least four stages: engagement, persuasion, active treatment, and relapse prevention/recovery (Osher & Kofoed, 1989). However, statistical models used to analyze stages of change data are often not appropriate. Sometimes, ordinal stages of change variables are analyzed as if they were continuous. The logistic regression for ordinal variables, called the proportional odds model, is more appropriate for this kind of data, but it assumes a common slope, which implies that the effect of explanatory variables on an ordinal outcome variable is the same from one level to the next for all levels. This is not a realistic assumption for some research problems. Moreover, the proportional odds assumption is seldom satisfied statistically.

Recently, the proportional odds model for ordinal data has been extended to a nonproportional odds model, or a partial proportional odds model, by relaxing the common slope assumption (Peterson & Harrell, 1990). Under this extended model, a subset of the explanatory variables is not required to have proportional odds. However, because of the unavailability of corresponding software, this new development has not received much attention in practice. More recently, the partial proportional odds model has been incorporated and further extended to the framework of the thresholds of change model (TCM) for analyzing stages of change data for both single-level and multilevel cases (Hedeker, Mermelstein & Weeks,

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1999; Hedeker & Mermelstein, 1998). The software for conducting TCM is also available now (Hedeker & Gibbons, 1996).

In this paper, we illustrate an application of TCM by analyzing data from a clinical trial of assertive community treatment for patients with co-occurring severe mental illness and substance use disorder in the State of New Hampshire. The response variable is the Substance Abuse Treatment Scale (SATS; McHugo, Drake, Burton, & Ackerson, 1995). The SATS has eight ordered response categories, but for this analysis it was recoded into three ordered levels: engagement/persuasion, active treatment, and recovery/relapse prevention. The variable with three levels is more manageable in using TCM, and it is theoretically meaningful because the two transition points correspond to widely recognized phases of recovery. The explanatory variables are gender and group, assertive community treatment (ACT) or standard case management (SCM). ACT is a more intensive treatment and is considered the "experimental" group; SCM is traditional treatment and is considered the "control" group. The purpose of the paper is to examine how gender and group influence the clients' movement through three stages of substance abuse treatment.

HOMOGENEOUS THRESHOLD OF CHANGE MODEL

Ordinal response variables are usually analyzed with logistic regression. Logistic regression for ordinal variables can be formulated in terms of either the cumulative logit model (Agresti, 1989, 1990) or the threshold of change model (Hedeker et al., 1999; Long, 1997). In terms of the cumulative logit model, for J ordinal categories, we can form $J-1$ cumulative logits. A model for the jth cumulative logit looks like an ordinary logit model for a binary response in which categories 1 to j combine to form a single category, and categories $j+1$ to J form a second category (Agresti, 1996). This model can be expressed in the following form:

$$\log\left[\frac{p(y \le j)}{1-p(y \le j)}\right] = \log\left[\frac{p_1+\cdots+p_j}{p_{j+1}+\cdots+p_j}\right]$$
$$= a_j + \sum B_i X_i$$
$$j = 1, \ldots, J-1 \text{ cumulative logits}$$
$$i = 1, \ldots, k \text{ variables}$$

For $J = 3$, for example, two logit models are needed:

$$\log\left[\frac{p_1}{p_2+p_3}\right] = a_1 + \sum B_i X_i$$
$$\log\left[\frac{p_1+p_2}{p_3}\right] = a_2 + \sum B_i X_i$$

In this model, the intercept parameter, α_j, is different for the j categories. As j increases, α_j increases, reflecting the increase in the logits as additional probabilities are added into the numerator. The parameter β_i describes the effect of X, an explanatory variable, on the log odds of response in category j or below. If $\beta_i > 0$, the cumulative probability tends to be higher at higher values of X. That is, the likelihood that Y is below any fixed level is relatively greater at higher values of X (Agresti, 1989). The important feature of this model is that the parameter β_i is assumed to be the same for all categories of Y. Because β_i has a constant value for each of the $J-1$ cumulative logits, this model is termed the proportional odds model.

The same proportional odds model can be conceptualized in terms of threshold of change. For this formulation, observed ordinal variables are viewed as the manifestation of, and categorization of, an underlying latent (unobservable) continuous variable. If the observed ordinal variable has J ordered categories, there should be $J-1$ thresholds separating individuals into J categories or stages. That is, individuals are classified into various ordered categories, or stages of change, according to "cut-off points," or "thresholds" on the continuous latent variable. For example, an individual is placed in category j $(Y = j)$ if the individual's stage of change exceeds threshold value γ_{j-1}, but does not exceed threshold value γ_j.

The TCM can be expressed in the same form as the cumulative logit model, but the interpretation of the coefficients is different. The coefficients of the model are evaluated in terms of their effect on either lowering or raising the threshold of change. Using the notation of Hedeker et al. (1999), if we let γ denote a threshold, then for an ordinal variable with three categories, we can represent two threshold models:

$$\gamma_1 = \alpha_1 + \sum \beta_i X_i$$
$$\gamma_2 = \alpha_2 + \sum \beta_i X_i$$

The α_j parameter serves as a base threshold, or as the category boundaries that define the level of response variable, Y, for the reference group. The coefficient β_i represents the effect of explanatory variables on either or both thresholds. Notice that β_i has no subscript j here, that is, the effect of X_i on both thresholds is assumed to be the same for this model. If $\beta_i < 0$ for a particular explanatory variable, then this variable lowers both thresholds and thus has a positive effect in moving an individual from a lower stage to a higher stage. If $\beta_i > 0$, then this particular variable raises the threshold and therefore has negative effect on outcome. If $\beta_i = 0$, then the explanatory variable has no effect.

The concept behind the TCM can be better illustrated graphically (Hedeker et al., 1999). This model is based on the following cumulative logistic distribution function:

$$p = 1/(1 + \exp^{-\gamma})$$

Based on the logistic response function in its standard form with mean 0 and variance of $\pi^2/3$, for a model with three ordered categories and two thresholds, we can plot a logistic distribution function as depicted in Fig. 1.

In Fig. 1, consider our response variable, the SATS with three stages: engagement/persuasion, active treatment, and recovery/relapse prevention. Suppose the first threshold, γ_1, the active treatment threshold, has a value of $-.5$, then the probability of a response below the active treatment threshold is $p = 1/(1 + \exp^{-(-.5)}) = .38$. Suppose the second threshold, γ_2, the recovery/relapse prevention threshold, has a value of 1.5, then the cumulative probability of a response below the second threshold is $p = 1/(1 + \exp^{-1.5}) = .82$. The probabilities of crossing the two thresholds are $1 - .38 = .62$, and $1 - .82 = .18$, respectively. Thus, it is harder to cross the second threshold, the recovery/relapse prevention threshold, than the first threshold, the active treatment threshold.

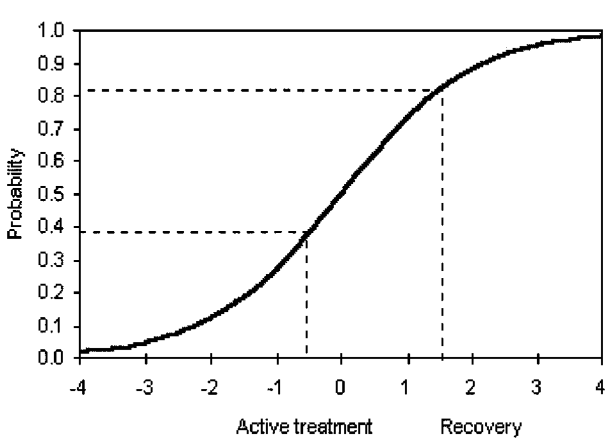

Fig. 1. Cumulative logistic distribution with two thresholds.

The thresholds illustrated in Fig. 1 are the base thresholds because there are no explanatory variables in the model. To demonstrate how an explanatory variable affects the base threshold, consider the simple threshold of change model with gender as the only explanatory variable:

$$\gamma_1 = \alpha_1 + \beta \text{ Gender}$$

$$\gamma_2 = \alpha_2 + \beta \text{ Gender}$$

If we code male $= 0$ and female $= 1$, then the base threshold and corresponding probabilities that we discussed earlier are for the males. Suppose the effect of gender is the same for both thresholds, and both thresholds are lowered by 1.5 units for females. That is, the active treatment threshold and the recovery threshold for males are $-.5$ and 1.5, but for females they are -2 and 0 respectively. Thus, the probability of a response below the active treatment threshold for females is, $p = 1/(1 + \exp^{-(-2)}) = .12$; or the probability for females to cross the active treatment threshold is $1 - .12 = .88$. The probability for a female to be classified as below the recovery threshold is, $p = 1/(1 + \exp^{0}) = .5$, and therefore the probability for females to cross the recovery threshold is also $1 - .5 = .5$. Thus, females have a higher probability of crossing both thresholds than males (.88 vs. .62 & .50 vs. .18). Converting these probabilities into odds, the odds for males to cross both thresholds are $.62/(1 - .62) = 1.63$ and $.18/.82 = .22$, and the odds for females to cross both thresholds are $.88/(1 - .88) = 7.3$ and $.5/.5 = 1.0$, respectively. The odds ratio comparing females to males is the same for both thresholds, that is, $7.3/1.63 = 1/.22 = 4.5$, meaning that females are 4.5 times more likely to cross both thresholds than males. The homogeneous TCM with gender as the only explanatory variable is illustrated in Fig. 2.

HETEROGENEOUS THRESHOLD OF CHANGE MODEL

The model described earlier is called the homogeneous threshold of change model, because the effects of explanatory variables are assumed to be the same across the thresholds. This model is really the same as the proportional odds model, except that it is conceptualized in terms of thresholds of change. Homogeneous TCM, or the proportional odds model, is not applicable for some research problems. The effect of explanatory variables may not be constant across

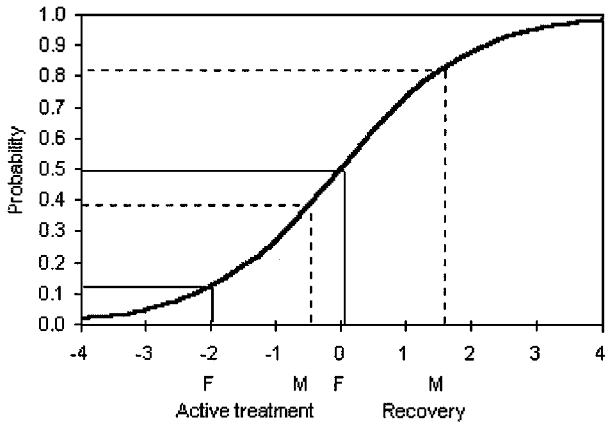

Fig. 2. TCM with homogeneous gender effect.

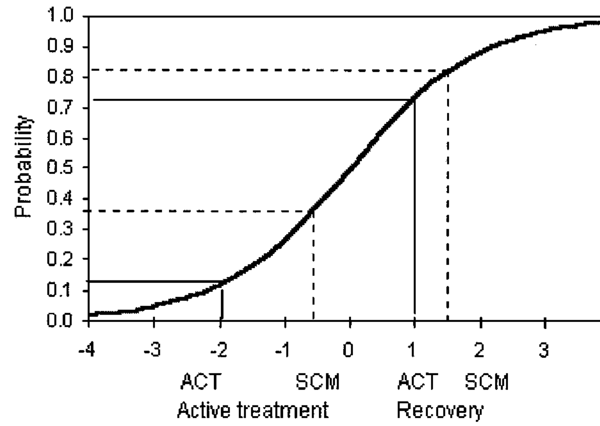

Fig. 3. TCM with heterogeneous group effect.

the thresholds. Moreover, if the proportionality assumption is violated for a particular data analysis, homogeneous TCM should not be used at all.

With recent developments in partial proportional odds theory (Peterson & Harrell, 1990), homogeneous TCM has been extended to heterogeneous TCM (Hedeker et al., 1999), in which a set of the explanatory variables is not assumed to have proportional odds, or homogeneous effects, on thresholds. That is, in this extended model, some variables may still be assumed to have homogeneous effects, but others are allowed to have various effects across thresholds. For a response variable with two thresholds, heterogeneous TCM can be written as:

$$\gamma_1 = \alpha_1 + \sum \beta_i X_i + \sum \beta_{1i} X_i$$
$$\gamma_2 = \alpha_2 + \sum \beta_i X_i + \sum \beta_{2i} X_i$$

where the first set of coefficients, $\sum \beta_i X_i$, is assumed to be the same across thresholds, but the second set of coefficients, $\sum \beta_{ji} X_i$, is allowed to be different for two different thresholds.

In our case, we have two explanatory variables, gender and group. Suppose we assume that the effect of gender is the same across thresholds, but the effect of group is threshold-specific. For example, the "hurdle" for the ACT group to cross the first threshold (active treatment) may be much lower than for the SCM group, but they may be very close at the second threshold (recovery), as illustrated in Fig. 3. In this case, the treatment group (ACT) may be more effective in moving clients from the engagement stage to the active treatment stage. That is, the ACT group may have a higher probability of crossing the first threshold than the control group (SCM), but there may be no significant difference between the groups in the likelihood of crossing the second threshold. Alternatively, as illustrated in Fig. 4, the hurdles to cross the first threshold for the two groups may be very close, but it is significantly lower for ACT group at the second threshold. Thus, the ACT intervention may be more helpful in getting a client to cross the second threshold, but its effect may not be different from the SCM intervention in terms of crossing the first threshold.

AN APPLICATION

Setting and Data

Data for this analysis are from the New Hampshire Dual Diagnosis Study, which was a longitudinal, randomized clinical trial (Drake et al., 1998). Two hundred twenty-three eligible persons

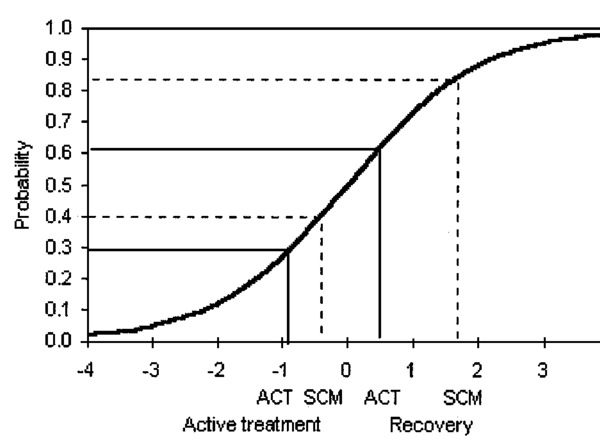

Fig. 4. TCM with heterogeneous group effect.

with co-occurring severe mental illness and substance use disorder from seven community mental health centers in New Hampshire were randomly assigned to two treatment groups: assertive community treatment (ACT) and standard case management (SCM). The clients were interviewed every 6 months for 3 years, and 203 completed the study. For this analysis, data at the endpoint assessment (36 months) are used.

Measures and Variables

The Substance Abuse Treatment Scale (SATS), which was a primary outcome variable in the NH Dual Diagnosis Study, is used as the response variable for this analysis. The SATS is an 8-point scale that indicates progression from treatment engagement toward recovery: 1–2 = early and late stages of engagement, 3–4 = stages of persuasion, 5–6 = stages of active treatment, and 7–8 = stages of recovery and relapse prevention (McHugo et al., 1995). The SATS was designed as a clinician-rated scale, and the clinician is asked to use all available information on the client to make a rating in one of the eight, behaviorally anchored categories. Information on alcohol and drug use, motivation for change, and treatment engagement is combined to make the rating. The SATS is based on a four-stage model that was proposed for dual diagnosis treatment programs (Osher & Kofoed, 1988). It can be used clinically to prescribe stage-appropriate treatments, and it can be used as either a process or an outcome measure for research purposes. Although ratings on the SATS are in four ordered stages of treatment, progress through them does not have to occur in a linear or sequential way for a given individual. Some individuals skip stages; some cycle among them. Yet, for most individuals with dual disorders, recovery from substance abuse proceeds through the four stages, and thus the question addressed in these analyses concerning progress from one stage to the next is a meaningful one.

The SATS ratings used here are based on researcher rather than clinician (i.e., case manager) ratings. After 3 years of data had been collected, a team of researchers reviewed all available data for each participant and arrived by consensus at ratings of alcohol use, drug use, and stage of treatment. The data included extensive interviews with participants, urine toxicology results, and case manager ratings, obtained every 6 months; and thus, the consensus SATS ratings are the most valid indicator of substance use and treatment status in this study. Because there were only a few clients who were still at the engagement stage at the end of the 3 years, we collapsed the engagement and persuasion stages into one category. We also collapsed the two levels within each major stage of recovery. Thus, the recoded scale has three categories, representing different stages toward recovery: engagement and persuasion, active treatment, and recovery/relapse prevention. To be brief, we call the three stages early treatment, active treatment, and recovery.

For simplicity, only two explanatory variables, gender and group (ACT vs. SCM), were used for this analysis. An indicator coding scheme was used for the two variables, that is, 1 = female and 0 = male for gender, and 1 = ACT and 0 = SCM for group. ACT is an innovative treatment strategy and is considered the "experimental" group; SCM is a conventional treatment strategy and is considered the "control" group.

Analysis and Results

The bivariate relationships between stage of substance abuse treatment and gender and group are displayed in Table 1. The observed percentages in the table indicate that females are more likely to move across both the active treatment and the recovery thresholds than males (29.4% & 39.2% for females vs. 26.2% & 22.8% for males, respectively). However, the effect of group is somewhat mixed: the ACT group

Table 1. Distribution of Gender and Group by Stages of Change at 36-Month Assessment

Explanatory variables	Stages of change: Pre-treatment ($N = 92$)	Active treatment ($N = 54$)	Recovery ($N = 54$)
Gender			
Female	16 (31.4)	15 (29.4)	20 (39.2)
Male	76 (51.0)	39 (26.2)	34 (22.8)
Group			
ACT	44 (42.7)	34 (33.0)	25 (24.3)
SCM	48 (49.5)	20 (20.6)	29 (29.9)

Note. Values in parentheses are percentage values.

Table 2. Observed Cumulative Odds for Crossing Thresholds

Explanatory variables	Active treatment, $(2 + 3)/1$	Recovery, $3/(1 + 2)$
Gender		
Female	35/16 = 2.19	20/31 = .65
Male	73/76 = .96	34/115 = .30
F/M odds ratio	2.19/.96 = 2.28	.65/.30 = 2.20
Group		
ACT	59/44 = 1.34	25/78 = .32
SCM	49/48 = 1.02	29/68 = .43
ACT/SCM odds ratio	1.34/1.02 = 1.32	.32/.43 = .75

is more likely to move from the pretreatment stage to the active treatment stage than the SCM group (33.0% for ACT vs. 20.6% for SCM), but less likely to move from the active treatment stage to the recovery stage than the SCM group (24.3% for ACT vs. 29.9% for SCM).

Based on data in Table 1, the observed or marginal effects of gender and group on the two thresholds can be derived. As indicated in Table 2, females are more likely to cross both thresholds than males (OR = 2.28 and 2.20 respectively). Different from gender, the ACT group is more likely to cross the first threshold (OR = 1.32) but less likely to cross the second threshold (OR = .75).

The observed percentages and odds ratios provide useful information about the bivariate relationships between variables. To understand these relationships better, a formal statistical model is needed. For this study, because we have two explanatory variables, the threshold of change model can be written as:

$$\gamma_1 = \alpha_1 + \beta_{11} \text{ Gender } + \beta_{12} \text{ Group}$$
$$\gamma_2 = \alpha_2 + \beta_{21} \text{ Gender } + \beta_{22} \text{ Group}$$

Given the indicator coding for the explanatory variables, gender and group as described earlier, α_1 and α_2 represent the active treatment threshold and the recovery threshold for males in the SCM group. β_{11} and β_{21} represent the gender effect on both thresholds, and β_{21} and β_{22} represent the group effect on both thresholds. Therefore, $\alpha_1 + \beta_{11}$ and $\alpha_2 + \beta_{21}$ represent the two thresholds for females, and $\alpha_1 + \beta_{12}$ and $\alpha_2 + \beta_{22}$ represent the two thresholds for the ACT group.

We have run four models for this data set using MIXORE, the updated version of MIXOR by Hedeker and Gibbons (1996). The results are summarized in Table 3.

Model (1) in Table 3 is a homogeneous threshold change model; the effects of gender and group on both thresholds are assumed to be the same (i.e., $\beta_{11} = \beta_{21}$ & $\beta_{12} = \beta_{22}$). In this model, $\alpha_1 = .10$ for the active treatment threshold, and $\alpha_2 = 1.29$ for the recovery threshold. These are thresholds for males in the SCM group. The gender effect, $\beta_{11} = \beta_{21} = -.81$, is statistically significant at $p < .01$. This means that both thresholds ($.10 - .81 = -.71$ & $1.29 - .81 = .48$) for females are significantly lower than those for males, holding the effect of group constant. By converting the coefficient $-.81$ into an odds ratio of .44 ($\exp^{-.81} = .44$), we see that females are $1/.44 = 2.27$ times more likely to cross both thresholds than males. Thus, females tend to show more rapid progress toward recovery in substance abuse treatment than males, regardless of group.

The group effect for both thresholds is $\beta_{12} = \beta_{22} = -.11$, and the corresponding odds ratio is .89. This means that the ACT group is 1.12 times (1/.89) more likely than the SCM group to cross both thresholds, but this difference is not statistically significant.

Model (2) assumes an equal group effect, but differential gender effects on the two thresholds. The

Table 3. Parameter Estimates for Thresholds of Change Model

	Effects of gender & group on both thresholds			
Thresholds parameters	Group = fixed; Gender = fixed (1)	Group = fixed; Gender = vary (2)	Group = vary; Gender = fixed (3)	Group = vary; Gender = vary (4)
Active treatment threshold				
Intercept	0.10	0.10	0.21	0.22
Gender (female = 1)	−0.81**	−0.83*	−0.81**	−0.86*
Group (ACT = 1)	−0.11	−0.11	−0.33	−0.33
Recovery threshold				
Intercept	1.29	1.28	1.11	1.09
Gender (female = 1)	—	−0.79*	—	−0.75*
Group (ACT = 1)	—	—	0.24	0.25
−2 log L	418.44	418.43	414.59	414.48

$^*p < .05$. $^{**}p < .01$.

estimated coefficients for gender, β_{11} and β_{21}, equal $-.83$ and $-.79$, respectively. Corresponding odds ratios are 2.29 [$1/\exp^{(-.83)}$] and 2.20 [($1/\exp^{(-.79)}$]. Note that the estimated odds ratios are quite similar to the observed odds ratios derived in Table 2 (2.28 and 2.20). The difference between the estimated two coefficients is .042, which is not statistically significant ($p = .90$). The -2 log likelihood statistic for this model is 418.43, which is almost identical to that of Model (1) (418.44). Therefore, gender satisfies the common coefficient assumption; Model (2) with a differential gender effect is not necessary.

In Model (3), we assume that the gender effect is proportional but that the group effect is nonproportional for the two thresholds. The estimated group effect for Threshold 1 (β_{12}) is $-.33$, and for Threshold 2 (β_{22}) is .24. Corresponding odds ratios are 1.39 [$1/\exp^{(-.33)}$] and .78 [$1/\exp^{(.24)}$]. Again the estimated odds ratios from the model are very similar to the observed odds ratios (1.32 and .75) reported in Table 2. The estimated and observed odds ratios do not agree exactly, because the observed ratios are computed without controlling for the other variable (i.e., unadjusted). The results from Model (3) indicate that the ACT group lowers the first threshold, but raises the second threshold. Thus, group has opposite effects here, although neither of these effects is statistically significant ($p = .26$ and .45, respectively). The estimated difference between the two effects is .57 ($p = .0496$). The -2 log likelihood statistic equals to 414.59 for this model. Compared with Model (1), this yields a likelihood ratio $\chi^2 = 418.44 - 414.59 = 3.85$, and the p value (.0496) is slightly below the .05 level of significance. Thus, we conclude that the group effect is not the same for both thresholds in this population.

In Model (4) we let both group and gender have heterogeneous effects. This model yields -2 log likelihood score $= 414.48$. Comparing with Model (3), the likelihood ratio, $\chi^2 = 414.59 - 414.48 = .11$, which is not statistically significant ($p = 0.74$). Therefore, Model (3) is preferred to Model (4), because it is more parsimonious.

To sum up, Model (3) with a homogeneous gender effect and a heterogeneous group effect on thresholds is the most appropriate threshold of change model for these data. According to the parameter estimates from this model, we conclude that gender has a significant, and homogeneous, effect on both thresholds of the outcome variable—the three-level Substance Abuse Treatment Scale. Females are more successful in moving from the pretreatment stage to the active treatment stage, and also from the active treatment stage to the recovery and relapse prevention stage, relative to males. The group effect is mixed; the ACT group is more successful in crossing active treatment threshold, but less successful in crossing the recovery threshold, relative to the SCM group. Although the difference between the two effects is statistically significant, the effect of group on each threshold is not.

DISCUSSION

TCM is an extension of the existing proportional odds model for ordinal data. The major feature of this model is its focus on the thresholds that separate the ordered stages. The effect of an explanatory variable can be assessed in terms of its role in either raising or lowering the "height" of the base thresholds. A more important feature of this model is that it allows a set of explanatory variables to exert differential effects on the different thresholds. This feature makes the threshold of change model a more appropriate statistical tool for modeling many practical problems in mental health and other research areas. With the current software (Hedeker & Gibbons, 1996), using the more appropriate statistical technique, TCM, for studying stages of change phenomena becomes possible now for applied researchers. One potential limitation about TCM, however, must be mentioned. That is, when an explanatory variable is continuous, allowing it's effect to be differential on different thresholds may lead to unreasonable results for some values of the variable. Technical explanation for this caveat is beyond this paper. Interested readers are referred to Hedeker et al.'s paper (1999) for details.

We applied this innovative TCM to analyze the data from a clinical trial of assertive community treatment for patients with co-occurring severe mental illness and substance use disorder. The response variable used for this analysis is the recoded Substance Abuse Treatment Scale with three ordered levels: pretreatment, active treatment and recovery. The explanatory variables are gender and group (ACT vs. SCM). We found that gender exerts constant and significant effects on both thresholds, that is, both the active treatment threshold and the recovery threshold are lower for females. The group effect was mixed; ACT (treatment group) lowered the active treatment threshold, but raised the recovery threshold. This mixed effect of group cannot be detected from the conventional proportional odds model. In terms of the latter model, group is assumed to have a common effect on both thresholds, and the estimated common effect is $-.11$, suggesting that ACT lowered both thresholds. This is a misleading conclusion because, as indicated in Model (3), the ACT group lowered the first threshold but raised the second one.

One caution about this specific example and the findings about the group effect is worth mentioning. As a first step in applying this threshold of change model, we only used the data at one assessment point, the 36-month assessment of the 3-year study. In our longitudinal study, we found that the ACT group had a positive and marginally significant effect ($p < .10$) on stages of substance abuse treatment (Drake et al., 1998). To verify these conclusions, a threshold of change model for longitudinal data with more explanatory variables should be conducted. Recently, the mixed-effects ordinal regression model for estimating either clustered or longitudinal thresholds of change has been developed (Hedeker & Mermelstein, 1998), and using this mixed-effects threshold of change model to analyze the longitudinal substance abuse treatment data will be our next step.

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