Chapter Three

Method

I. Subjects

The total sample used in this study consisted of participants recruited from two separate populations: (a) outpatients of a psychiatric clinic who were diagnosed as suffering from depression as the depressed sample, and (b) undergraduates as the non-depressed sample.

A. Depressed sample

A total of 240 subjects were selected from outpatients who visit the psychiatric clinic at Taipei Municipal Hoping Hospital during July and August in 2004 and were diagnosed as having depression symptoms. The self-reported instrument utilized in this study was administrated by the researcher while the severity of depression was diagnosed by a psychiatrist.

B. Non-depressed sample

A total of 321 Taiwan undergraduates from National Cheng-Chi University, National Taiwan University of Arts, National Taipei Teacher College, and Nation Pingtung Teacher College were recruited in this study as non-depressed sample.

II. Measures

Beck Depression Inventory–II (BDI-II) (Beck et al., 1996) was adopted as the measure in study. BDI, specifically developed to address all of the nine DSM–IV criteria for a major depressive episode, is a self-reported instrument for measuring the severity of depression in adolescents and adults through items showing varying degrees of the main cognitive, affective, and physiological aspects of clinical depression. Participants circle the number (0 to 3) associated with the item that best describes how they had felt over the past two weeks. According to Beck et al. (1996), total BDI–II scores ranging from 0 to 13 represent normal to minimal depression, total scores from 14 to 19 are mild, total scores from 20 to 28 are moderate, and total scores from 29 to 63 are severe.

A number of studies have investigated the psychometric characteristics of the BDI–II with respect to both clinical and non-clinical populations. These studies have generally found that the BDI–II has high internal consistency (alpha coefficient > .90) and moderate to strong convergent validities with other self-reported measures, such as CES-D, the Reynolds Adolescent Depression Scale, and clinical rating scales of depression in adult and adolescent psychiatric patients, college students, and normal adults (Krefetz, Steer, Gulab, & Beck, 2002).

In this study, we adopted the Chinese version of BDI-II translated by Chen (2000). However, the norm for Chinese version is still not available now.

III. Scaling

This study proposed the Fuzzy Partial Credit Scaling (FPCS), combining fuzzy set theory and partial credit model, as an alternative scoring method. The following paragraph illustrated the procedures to complete FPCS. First, the differences between traditional scoring and fuzzy scoring were discussed. Second, the results of fuzzy scoring were used to complete FPCS.

A. Traditional and Fuzzy Scoring

Traditionally, subjects are forced to choose one of the alternatives (categories) for each item. This operation, from the perspective of philosophy, underlies the assumption inherited from binary logic. That is, each individual can be dichotomized into member (those that certainly belong to the set) and nonmember (those that certainly do not) of a set. In view of this, each subject belongs to exactly one of the alternatives (categories, sets) and, certainly, only one alternative is chosen to represent one's states or traits. Therefore, the membership degree that some individual belongs to a certain alternative is 1 or 0.

Nevertheless, fuzzy logic argues that membership degree that some individual belongs to a certain alternative (category) is a continuum value, gradual transition from 0 to 1, rather then a dichotomy, 0 or 1. According to this argument, in FPCS, subjects are free to choose more than one alternative for each item and, in turn, assign percentages on the chosen alternatives. The assigned percentages represent the degree of membership that some subjects belong to the category. Moreover, the sum of percentages of the chosen categories is restricted to 100%.

The percentages assigned to each category constitute the fuzzy scoring while the category assigned the most percentages is treated as the traditional scoring. Considering the specificity (the probability that diagnose test is positive when the subject has the disease), if there are two most assigned categories, we will take the maximum of categories as the traditional scoring. The traditional scoring will then be utilized as crisp data for PCM algorithms using the Winstep computer software (Linacre, 2005).

Table 3.2 shows the examples of fuzzy scoring and traditional scoring.

Table 3.1(a) Examples of Fuzzy and Traditional Scoring

	Assigned Percentages	Degree of Membership to Each Category (Fuzzy Scoring)	Traditional Scoring
Alternative 1*	80 %	.8	**1**
Alternative 2	20 %	.2	
Alternative 3	0 %	0	
Alternative 4	0 %	0	

Note. * indicates the category assigned the most percentages.

Table 3.1(b) Examples of Fuzzy and Traditional Scoring: Only One Category Chosen

	Assigned Percentages	Degree of Membership to Each Category (Fuzzy Scoring)	Traditional Scoring
Alternative 1	0 %	0	**3**
Alternative 2	0 %	0	
Alternative 3*	100 %	1.0	
Alternative 4	0 %	0	

Note. * indicates the category assigned the most percentages.

Table 3.1 (c) Examples of Fuzzy and Traditional Scoring: Two Most Assigned Categories

	Assigned Percentages	Degree of Membership to Each Category (Fuzzy Scoring)	Traditional Scoring
Alternative 1	50 %	.5	**2**
Alternative 2*	50 %	.5	
Alternative 3	0 %	0	
Alternative 4	0 %	0	

Note. * indicates the category assigned the most percentages.

B. Fuzzy Partial Credit Scaling

The procedures for Fuzzy Partial Credit Scaling were as follows:

Step 1: Subjects are asked to choose and assign percentages on alternatives of items. The sum of assigned percentages in each item must be constrained to 100%.

Step 2: Calculate the traditional scoring according to the procedures mentioned above.

Step 3: Calculate "step parameters" (δ_{ij}) defined in PCM as shown in Figure 3.1. The PCM algorithm (Masters & Wright, 1997) is shown in Equation 2.17.

Step 4: Fuzzify crisp data into fuzzy data by constructing triangle fuzzy numbers using step parameters estimated in Step 3.

We try to map linguistic variables, Alternatives 1 to 4, into corresponding reasonable normal fuzzy numbers $\tilde{A}$, $\tilde{B}$, $\tilde{C}$, and $\tilde{D}$, with triangular membership functions $\mu_{\tilde{A}}$, $\mu_{\tilde{B}}$, $\mu_{\tilde{C}}$ and $\mu_{\tilde{D}}$. These membership functions are shown in Figure 3.2.

The x-axis represents ability, usually ranging from -3 to 3; while y-axis represents degree of membership, ranging from 0 to 1.

In Figure 3.2, we first find the "step parameters" (δ_{ij}) estimated by PCM. We propose that subject with ability located between -3 and "step parameter 1" (δ_{i1}) will choose Alternative 1. For this reason, the triangular fuzzy number $\tilde{A}$= (-3, -3, δ_{i1}) with -3 and δ_{i1} being the lower and upper bounds, respectively, and -3 as the most likely value for $\tilde{A}$. In Figure 3.2, we draw a line segment from (-3, 1) to (δ_{i1}, 0) to characterize the membership of function of $\tilde{A}$.

Next, we propose that subject with ability located between "step parameter 1" (δ_{i1}) and "step parameter 2" (δ_{i2}) will choose Alternative 2 and the middle point between these two step parameters should receive the maximum degree of membership. Therefore, the triangular fuzzy number $\tilde{B}$= (δ_{i1}, ($\delta_{i1}+\delta_{i2}$)/2, δ_{i2}) with δ_{i1} and δ_{i2} being the lower and upper bounds, respectively, and ($\delta_{i1}+\delta_{i2}$)/2 being the middle point which is the most likely value for $\tilde{B}$. In Figure 3.2, we draw a line segment from (0, δ_{i1}) to (($\delta_{i1}+\delta_{i2}$)/2, 1) to represent the left leg and another line segment from(($\delta_{i1}+\delta_{i2}$)/2, 1) to(δ_{i2}, 0) to represent the right leg of the triangular fuzzy number.

Likewise, we proposed $\tilde{C}$= (δ_{i2}, ($\delta_{i2}+\delta_{i3}$)/2, δ_{i3}) and $\tilde{D}$= (δ_{i3}, 3, 3) to characterize the likelihood of Alternatives 3 and 4, respectively.

Step 5: Defuzzify fuzzy data into scalar using the center of gravity (COG) method. COG calculates the center of gravity of the support of the fuzzy number weighted by the membership grade.

The center of gravity of fuzzy set $\widetilde{X}$ with membership function $\mu_{\widetilde{A}}$, GR(X) =

$$\frac{\int_{-\infty}^{\infty} x\mu_x(x)dx}{\int_{-\infty}^{\infty} \mu_x(x)dx} \qquad (3.3)$$

For a triangular fuzzy number $\widetilde{X}$ (a, b, c), GR(X) = (a+b+c)/3(Zimmermann, 1996).

Step 6: Calculate the fuzzy observed scores.

After defuzzification, we calculate the fuzzy observed scores by multiplying the sum of membership degree of the set by its center of gravity.

A hypothesized example is shown in Table 3.3. In this table, an item of four alternatives with corresponding fuzzy sets $\widetilde{A} \sim \widetilde{D}$ is given. As noted previously, we estimate step parameters of PCM to construct fuzzy triangular numbers. Next, we calculate the center of gravity of these fuzzy numbers for defuzzfication. Finally, the fuzzy observed scores is obtained by weighing the sum of center of gravity by degree of membership.

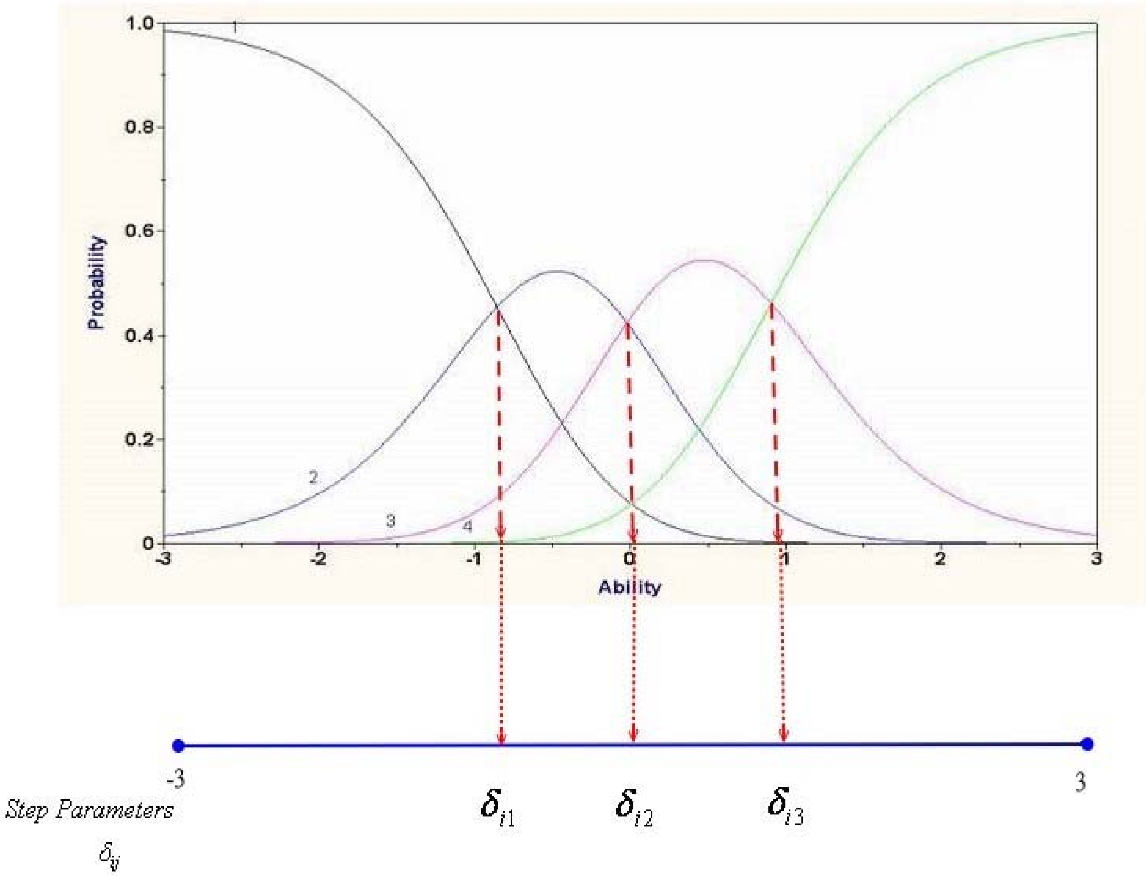

Figure 3.1 Calculations of Step Parameters

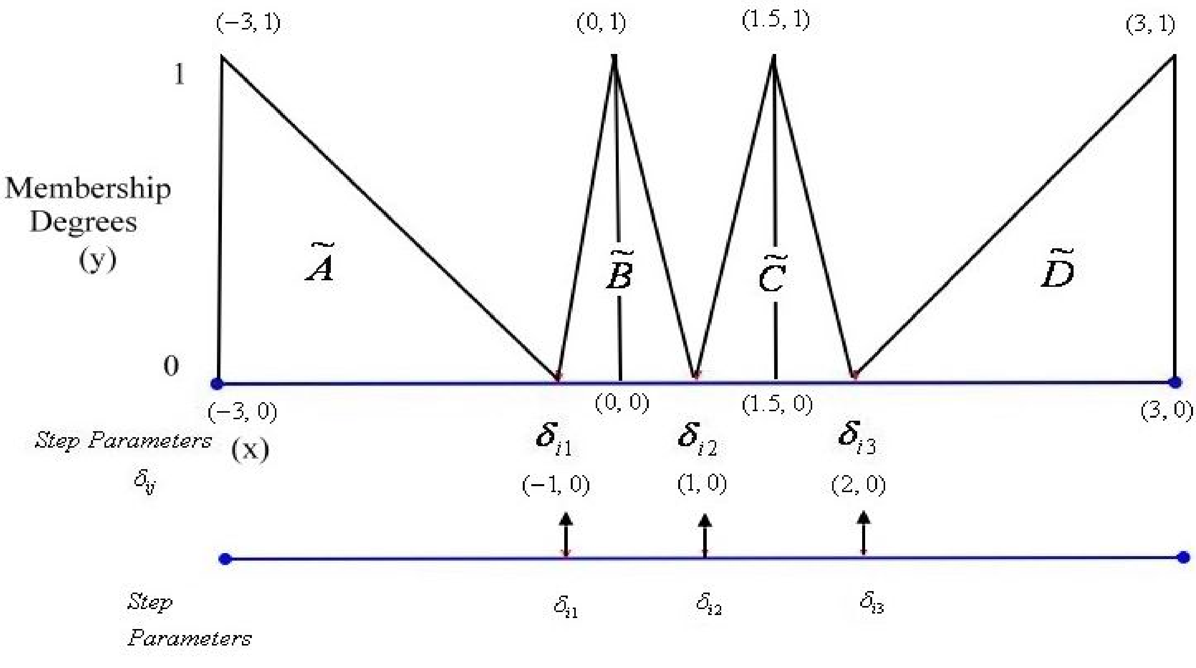

Figure 3.2 Constructions of Triangular Fuzzy Numbers

Table 3.2 A Hypothetic Example of FPCS

	Membership Degrees	Step Parameters (δ_{ij})	center of gravity of fuzzy set (GR)	The fuzzy observed scores
$\tilde{A}$ (Alternative 1)	.8	Lower Bound= -3	((-3)+(-3)+(-1))/3 = -2.333	**(.8 × -2.333) +(.2×2)= -1.4664**
$\tilde{B}$ (Alternative 2)	.2	δ_{i1} = -1	((-3)+(-2)+(-1))/3 = -2	
$\tilde{C}$ (Alternative 3)	0	δ_{i2} = 0	((-1)+(-.5)+0)/3= -.5	
$\tilde{D}$ (Alternative 4)	0	δ_{i3} = 1	(1+3+3)/3= 2.333	
		Upper Bound= 3		

IV. Procedures

Depressed participants were recruited from Taipei Municipal Hoping Hospital. Those who were diagnosed as suffering from depression were asked to complete the BDI. The self-reported instrument was administered by the researcher one subject at a time. After completing the instrument, a short interview was given to the subject to collect their feedback about items in the Chinese version BDI and about the new "fuzzy" method to fill out a scale.

Owing to multiple-assignment, it took 5 to 25 minutes for depressed outpatients to complete the BDI, which was longer than that for completing the original "crisp" BDI.

Non-depressed participants were recruited from undergraduates of pedagogy courses and they also completed the same self-reported instrument. To avoid contamination, undergraduates who meet cutoffs on BDI, 19 points according to traditional scoring, are excluded.

V. Analysis

The data analysis procedures for three studies were listed below:

A. Study One: Reliability of FPCM

Two different models, FPCS and traditional scoring, were compared to determine which model best described the data and exhibit better reliability. Analysis of covariance employing confirmatory factor analytic models was conducted using the LISREL 8.53 statistical software package. The following goodness-of-fit criteria were employed to evaluate model fits:

(1) The chi-square statistics (χ^2): χ^2 evaluates whether the unrestricted population variance/covariance matrix of the observed variables Σ is equal to the model-implied variance/covariance matrix Σ(θ). Owing to a dependency on sample size and assumption of multivariate normality, χ^2 should be used as a guideline of general fit rather than the only evaluation of model fit.

(2) The comparative fit index (CFI; Bentler, 1988): CFI employs noncentral χ^2 distribution and noncentral parameter. CFI is normed to the 0-1 range. Values great than .90 are often indicative of good-fitting models.

(3) The root mean square error of approximation (RMSEA; Brown & Cudeck, 1993): RMSEA estimates the lack of fit in a model compared with a saturated model. Values of .05 or less indicate a good-fitting model and values as high as .08 represent reasonable models.

Since reliability is defined as the proportion of true variance relative to total variance in SEM, the square correlations between the latent and observed variables are adopted as the measure of reliability.

B. Study Two: Validity of FPCS

Two different models, FPCS and traditional scoring, are compared to determine which model best predicts the odds of suffering from depression. Logistic regression analysis and discrimination analysis were conducted utilizing the SAS 9.13 statistical software package.

C. Study Three: Fuzzy c-means Clustering

Classical (crisp) clustering algorithms generally partition such that each object is assigned to exact one cluster. Often, however, objects can not adequately be assigned to one cluster when they are located between clusters. In the circumstances, fuzzy clustering provides a much more adequate tool for representing real-data structure (Zimmermann, 1996).

FCM algorithm was conducted using F-cut Fuzzy Partition Program developed by Lin (Lin, 2003b) to partition subjects according to their severity of depressed symptoms. The algorithm comprises the following steps (Bezdek, 1981; Zimmermann, 1996):

Step 1: choose c, (number of clusters, $2 \leqq c \leqq n$), m (exponential weight, $1 < m < \infty$). Initialize $\widetilde{U}^{(0)} \in M_{fc}$, set l=0.

Step 2: Calculate the c fuzzy centers $\{v_i^{(l)}\}$ by using $\widetilde{U}^{(l)}$, from condition

$$\sum_{i=1}^{c} \mu_{ik} = 1 \qquad (3.4)$$

and

$$v_i = \frac{\sum_{k=1}^{n} (\mu_{ik})^m x_k}{\sum_{k=1}^{n} (\mu_{ik})^m} \quad i = 1,2,\ldots c \qquad (3.5)$$

Step 3: Calculate the new membership matrix $\widetilde{U}^{(l+1)}$ by using $\{v_i^{(l)}\}$ from the condition:

$$\mu_{ik} = \frac{\left(\dfrac{1}{\left\|x_k - v_j\right\|^2}\right)^{1/(m-1)}}{\sum_{j=1}^{c}\left(\dfrac{1}{\left\|x_k - v_j\right\|^2}\right)^{1/(m-1)}} \quad i = 1,2,\ldots c;\ k=1,\ldots,n \qquad (3.6)$$

if $x_k \neq v_i^{(l)}$, else set $\mu_{jk} = \begin{cases} 1 & for \quad j = i \\ 0 & for \quad j \neq i \end{cases}$

Step 4: Choose a suit matrix norm and calculate $\Delta = \left\|\widetilde{U}^{(l+1)} - \widetilde{U}^{(l)}\right\|$.

If $\Delta > \varepsilon$, set $l=l+1$ and go to step2. If $\Delta \leqq \varepsilon$, then stop.

The cluster validity problems concern the general question of whether the underlying assumption such as cluster shape or number of clusters of a clustering algorithm are satisfied at all for the considered set (Hoppner, Klawonn, Kruse, & Runkler, 1999). The most acknowledged measures for judging the fuzziness of a clustering solution are partition coefficient F($\widetilde{U}$, c) (PC; Bezdek, 1981), and partition entropy H($\widetilde{U}$, c) (PE; Bezdek, 1981).The partition coefficient of $\widetilde{U}$ is the scalar (Zimmermann, 1996):

$$F(\widetilde{U}, c) = \sum_{k=1}^{n}\sum_{i=1}^{c}\frac{(\mu_{ik})^2}{n} \qquad (3.7)$$

The partition entropy of any fuzzy c-partition $\widetilde{U} \in M_{fc}$ of X, where $|X| = n$, is for $1 \leqq c \leqq n$

$$H(\widetilde{U}, c) = -\frac{1}{n}\sum_{k=1}^{n}\sum_{i=1}^{c}\mu_{ik}\log_e(\mu_{ik}) \qquad (3.8)$$