CALIBRATION AND VALIDATION OF THE BODY SELF-IMAGE QUESTIONNAIRE USING THE RASCH ANALYSIS

by

HYUK CHUNG

(Under the Direction of Ted A. Baumgartner)

ABSTRACT

The purpose of this study was to calibrate and validate the Body Self-Image Questionnaire using the Rasch analysis. The data from 1021 undergraduate students were used for this study. The Body Self-Image Questionnaire consists of 39 items under the nine factors related to the body image construct and a Likert-type five-point response scale for each item.

The data from each subscale of the questionnaire were initially calibrated using the rating scale model for investigating category function and item structure. Violations in category function were found from the initial calibrations for the fatness evaluation (FE), social dependence (SD), height dissatisfaction (HD), and investment to ideals (II) subscales, and the optimal categorization was determined for those subscales. The collapsed four-point categorization obtained by combining categories three and four functioned better than other combinations for the FE, SD, HD, and II subscales and the original categorization was retained for the other subscales. Three misfitting items were also identified and deleted from corresponding subscales for further analysis.

The revised categorization and item structure were cross-validated using a validation sample (n = 510) randomly selected from the total sample. Similar patterns of categorization

were observed and confirmed except for the categorization for the HD subscale. Hierarchical orders of item difficulties for the validation sample were identical to the total sample. To Provide evidence of construct validity, three groups were formed based on body mass index (BMI) scores and the means in logits for the three BMI-based groups were compared and contrasted. Overall discrimination among groups for each subscale was effective. The result showed that the underweight BMI group tended to endorse categories indicating higher satisfaction with body image while the overweight BMI group tended to endorse categories indicating lower satisfaction with body image. The findings from these analyses supported that the data fitted the rating scale model well in terms of fit statistics, and the rating scale model adequately contrasted items and participants according to their measures in logits. The rating scale model provided a way to transform the ordinal data into interval and to investigate the category function of Body Self-Image Questionnaire.

INDEX WORDS: Rasch analysis, Rating scale model, Optimal categorization, Rasch calibration, The Body Self-Image Questionnaire

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DEDICATION

Dedicated to the ultimate Giver who taught me not to lean on my own understanding.

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Finally, Thank God It’s Fulfilled!

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CHAPTER 1

INTRODUCTION

A rating scale with ordered response categories has been commonly used in physical education and exercise science (Fichter, & Quadflieg, 2003; Hansen & Gauthier, 1989; Kulinna, Cothran, & Regualos, 2003; Rowe, Benson, & Baumgartner, 1999). Most conventional procedures for developing scales include developing a number of items and assigning a response category to the items. Then, the instrument is administered to a sample and item statistics and personal measures are obtained from the item responses of the instrument. Finally, coefficient alpha is calculated and factor analysis is applied to the data to investigate the psychometric quality of the instrument (Zhu, 2001).

If these analysis procedures are used with ordinal data, however, these conventional procedures raise fundamental measurement issues which may cause critical problems in terms of interpretation and inference (Andersen, 1977; Bond & Fox. 2001; Merbitz, Morris, & Grip, 1989; Rasch, 1980; Wright, 1996; Wright & Linacre, 1989; Wright & Masters, 1982; Zhu, 1996). First, it is inappropriate to compute total scores from ordinal data. Because Likert scales are ordinal rather than interval, the data should not be summed. Second, selecting the number of response categories is mostly dependent on the researchers' knowledge and experience. Therefore, it is arbitrary to set a certain number of response category without an empirical test, which enables the researcher to determine the most appropriate categorization. Third, calibrations under the conventional procedure are often sample and item dependent. In traditional

item analysis, item difficulty is estimated based on the proportion of correct responses in a sample, and item discrimination is represented by the correlation between item scores and total test scores. Person ability also depends on the particular collection of items used in an instrument. Therefore, levels of item difficulty and person ability may change based on the characteristics of samples (i.e., the level of ability and homogeneity of a sample being tested). These dependencies make it difficult to have consistent research findings and to compare findings across studies with various samples. Last, items and respondents are calibrated on different scales in conventional procedures. For example, means and standard deviations of items are used for item investigation and total scores are used for respondents' summaries. Therefore, both facets, item difficulty and person ability, cannot be compared on the same metric.

Similar issues have been debated in fields such as psychology, education, and medical rehabilitation (e.g., Andrich, 1978; Merbitz, Morris, & Grip, 1989; Wright, 1996; Wright & Linacre, 1989), and many researchers have applied the Rasch analysis to ordinal data to solve these problems (Kirby, Swuste, Dupuis, MacLeod, & Monroe, 2002; Waugh, 2003). Originally, the Rasch model was developed for dichotomously scored items to construct objective measures that enable a researcher to define the difficulty of an item and the ability of an individual independent from population and items, respectively (Rasch, 1960/1980). Even though the Rasch model is also known as a one-parameter logistic model of item response theory (IRT), the early studies of the Rasch model were not closely related to IRT and Rasch barely referred to IRT literature in his studies. Rather, some researchers approached the Rasch model with IRT concepts. Andersen (1973) approached the Rasch model with conditional maximum likelihood estimation (MLE) procedures, and Masters and Wright (1984) described five Rasch families of latent trait models within the IRT framework. Further, Andrich (1978) extended the idea of the

Rasch modeling to a rating scale model in which items with ordered response categories can be analyzed.

From the various applications of the Rasch model to rating scales, several advantages of the Rasch analysis have been defined. First, the Rasch model provides a simple and practical way to construct linear measures from any ordered nominal data so that subsequent statistical analysis can be applied without a concern for linearity. Second, parameter estimations are independent from the individuals and items used. Third, testing results can be interpreted in a single reference framework because both item difficulty and individual ability are located on the same scale. Due to these features, it has been reported that the application of the Rasch model is advantageous to construct objective and additive scales (Bond & Fox, 2001).

In physical education and exercise science, some researchers have applied the Rasch model to rating scales for calibrating and optimal categorizing of instruments, and developing objective measures (Kulinna & Zhu, 2001; Looney, 1997; Looney & Rimmer, 2003; Zhu & Cole, 1996; Zhu & Kurz, 1994; Zhu, Timm, & Ainsworth, 2001). Although the advantages of the Rasch analysis have been introduced, it has not been widely used in the field because treating raw scores as interval measures sometimes seems to work due to the carefully designed interval-like response categories and the monotonous relationship between scores and measures in special situations. However, these cases are rare in practice and empirically not proven, so it is still preferable to convert raw scores to linear measures.

The interest in body image has increased as dissatisfaction with body image has been considered a contributory factor in the development of eating disorders (Smolak, 2002). A variety of instruments have been developed to measure the construct of body image. However, Rowe (1996) pointed out two problems with existing body image instruments. First, despite the

large number of instruments available, few were developed using rigorous methods such as investigating construct validity evidence. Second, even though some instruments were developed for measuring body image, they are measuring different constructs of body image or the term 'body image' is being used in different ways in those studies. For this reason, Rowe (1996) developed a scale, the Body Self-Image Questionnaire (BSIQ), for measuring the body image construct in a more comprehensive and systematic way.

Although the BSIQ was developed through four stages of elaborate investigations such as collecting items from a review of the literature and current instruments, revising items using exploratory factor analysis, defining factors and items using confirmatory factor analysis, and investigating construct validity, the fundamental measurement problems still exist in analyzing data from this ordinal scale. Therefore, applying the Rasch model to the BSIQ is necessary to provide a solution for current measurement concerns, such as linear measures and optimal categorization, and to define body image items and individual scores on the same metric.

Statement of Problem

Even though ordinal data are not sufficiently interval to justify researchers to do arithmetic calculations on the data, it is common in practice to analyze ordinal data as though they are interval measures. A measurement model that provides a way to construct linear measures from ordinal data has been introduced and extended for various applications since the 1960s and currently many computer programs are available for application of the model to rating scales. However, only a few studies have been done using the Rasch models in the physical education and exercise science fields and the measurement model has not been employed in developing and investigating body image scales.

The BSIQ consists of 39 items and a Likert-type 5-point response scale for each item. Even though validity of the BSIQ was investigated with various statistical techniques, the linearity of measures and the function of categorization have not been investigated. Therefore, it was required to transform the ordinal data to logits using IRT for analyzing subscale scores or conducting any further statistical analysis. Additionally, it was necessary to exam the categorization as to whether each response category would function as intended because optimal categorization was known to improve the quality of measurement.

Purpose of Study

The primary purpose of this study was to calibrate the BSIQ by transforming ordinal data into logits for investigating both item difficulty and person ability on the same continuum. The secondary purpose was to examine the categorization of each subscale of the BSIQ and to determine the optimal categorization for the subscales with problematic categorization. Through the Rasch analysis, it was expected that the Rasch analysis would provide an effective framework describing the nature of body image items and respondents' attribute on the same metric and improve the function of rating scale categorization.

Research Questions

During this study, the following research questions were addressed.

1. Will the data of the BSIQ fit the model in terms of Infit and Outfit?
2. Will the Rasch model calibration adequately contrast items and participants in terms of item difficulty and the level of the attribute?
3. Is the response categorization of the BSIQ functioning as intended in terms of frequencies, average measures, step calibrations, and Outfit statistic? When any violation or misfitting is found in category function, will the collapsing procedure solve the

problem of the categorization? And which pattern of collapsing combinations is most appropriate to each subscale of the BSIQ?

4. Will the Rasch calibrated item and person parameters and the revised categorization be stable when a smaller sample is calibrated?

Delimitations of the Study

1. Data from a previous study were used for this study. The data were collected from undergraduate students with ages 17 to 25. The students were participating in at least one of basic physical education activity classes.
2. The rating scale model was used in the present study with the assumption that the effect of guessing was minimal and the item discrimination was identical across the items.
3. In collapsing procedure, the linguistic aspects of category definitions such as word clarity, substantive relevance, and conceptual sequence, were assumed to be plausible. So, only numerical and empirical aspects of categorization such as hierarchical order of average measures, step advance, and category fit statistics were considered in determining optimal categorization.

Definition of Terms

Calibration. Traditionally, it refers to a process of translating scores obtained from several tests of different difficulty levels to a single common score scale (Chang, 1985). Scaling is an interchangeable term indicating the development of systematic rules and meaningful units of measurement for quantifying empirical observations (Crocker & Algina, 1986). In the Rasch analysis, calibration refers to a process of converting raw scores to logits to determine the values of item difficulty and person ability in a metric for the underlying latent trait.

Rating scale model. It is one of the Rasch family of models developed by David Andrich (1978). The rating scale model can be applied to polytomous data obtained from ordinal scales or Likert scales. In the item response theory framework, the rating scale model is categorized as a one-parameter logistic model.

Optimal Categorization. In the Rasch analysis, the term optimal is relative to the original categorization for an instrument rather than the best categorization. Therefore, the optimal categorization refers to a categorization which produces the hierarchical order in average measures and step calibrations, and better fit statistics and separation statistics than other combinations of categorization.

Fundamental measurement. It refers to the idea that requires an ordering system and the characteristics of additivity in assigning numbers to objects to represent their properties. The Rasch model is a type of additive conjoint measurement which satisfies these requirements of fundamental measurement.

Linearity. It refers to the idea or the characteristics of measurement which is additive such as length and weight. In the Rasch analysis, the qualitative variations of the raw scores are transformed into logits on a linear scale to have the characteristics of linear measure.

Invariance. This term indicates the maintenance of the identity of a variable from one occasion to the next. In theory, the process of measurement can be repeated without modification in different parts of the measurement continuum due to the two dominant advantages of the Rasch model which provides sample–free item calibration and test-free person measurement. For example, if two item difficulty estimates obtained from different groups for any particular item are transformed and placed on a common metric, the two item difficulty estimates should have approximately the same values.

Latent trait. This term refers to certain human attributes that are not directly measurable. In the theory of latent model, a person's performance can be quantified and the values are used to interpret and explain the person's test response behavior. Frequently, trait and ability are used interchangeably in the literature.

Logit. The abbreviation of log odds unit. The unit of measurement that results when the Rasch model is used to transform raw scores obtained from ordinal data to log odds ratios on a common interval scale. A logit has the same characteristics of an interval scale in that the unit of measurement maintains equal differences between values regardless of location. The value of 0.0 logit is routinely allocated to the mean of the item difficulty estimates (Bond & Fox, 2001).

Probabilistic. Given that all the possible influences on a person's performance cannot be known, the outcomes of the Rasch model are expressed mathematically as probabilities. For example, the Rasch measurement is probabilistic; the total score predicts with varying degrees of certainty which items were correctly answered.

CHAPTER 2

RELATED RESEARCH

The primary purpose of this study was to calibrate the BSIQ (Rowe, 1996) by transforming the raw data from an ordinal scale into logits for investigating both item difficulty and person ability (i.e., body image satisfaction) on the same continuum. The secondary purpose was to determine the optimal categorization of the BSIQ. Presented in this chapter are an overview of rating scales, the Rasch models, the Rasch model assessment, the Rasch calibration, optimal categorization, and measurement of body image.

Overview of Rating Scales

Rating scales with response options are designed to extract more information out of an item than information obtained from an item with a dichotomous scale. A rating scale with response options is classified as an ordinal scale based on Stevens' (1946) classification system. Likert scales have been the dominant type of categorizations in rating scales to collect attitude data. A Likert scale was originally expressed with five possible response options; strongly disagree, disagree, neutral, agree, and strongly agree. In general, each item is presented to a participant with a statement and a five-point scale. Then, the participant is asked to choose a response from the five-point scale. This ordinal scale does not provide either a common unit of measurement between scores or the origin that indicates absolute zero but provides only an order between scores (Baumgartner, Jackson, Mahar, & Rowe, 2003). Due to the absence of equal

measurement units and unknown distance between scores, responses in an ordinal scale should not be added for obtaining total or subscale scores.

Problems in Analyzing Ordinal Data

Many instruments and questionnaires assessing attitude have used on rating scales and the number of studies using a rating scale is increasing as new instruments and questionnaires are being developed. The procedures for developing rating scales have been well introduced in many studies in order to develop a sound understanding of complex models and theories (Benson & Nasser, 1998; Crocker, Llabre, & Miller, 1988; Dunbar, Koretz, & Hoover, 1991; Ennis & Hooper, 1988; Klockars & Yamagishi, 1988). However, the appropriate procedures for analyzing rating scales with ordinal scales have not been well introduced and the procedures have been ignored. As a result, ordinal integer labels (e.g., strongly agree = 5) from rating scales are commonly analyzed as though they were interval measures and means and total scores are calculated.

According to Bond and Fox (2001), measures must be objective abstractions of equal units to be reproducible and additive. If total scores are obtained from a scale without meaningful order or equal measurement units, they will not be meaningful for tests and analyses. Because order and equal distance between score units are critical features of addition and subtraction, a rating scale which has only one feature is not summative. Indeed, total scores are the sums of all responses in the scales, which are ordinal, so analyzing total scores is not appropriate. Thus, misuses of means and total scores generated from ordinal scales are often misleading. Stevens (1946) suggested that the statistics involving means and standard deviations should not be used with ordinal scales because the ordinal scale arises from the operation of rank-ordering procedure. In other word, although 4 is greater than 3 and 2 is greater than 1 in terms of the level

of the trait being measured, the sum of 4 and 1 may not necessarily be equal to the sum of 3 and 2 because the difference between 1 and 2 may not be identical to the difference between 3 and 4 due to the absence of the linearity of measures. Crocker and Algina (1986) also suggested that total score from a scale without meaningful order and equal measurement units cause confusion when it is used for determining validity or reliability of an instrument because it is virtually impossible to detect whether a problem (e.g., low coefficient) is caused by inappropriate numeric properties or inadequate validity or reliability of the instrument.

The ideas of fundamental measurement started being raised by some researchers in the early 1900s. Thorndike (1926) indicated the need for an equal-interval scale in which one step increment of integer labels would represent amounts increasing by a constant difference. Thurstone (1925, 1927) suggested using an absolute scale that approximates an equal-interval scale, even though it was pointed out that the absolute scale lacked objectivity due to the dependency on the ability distribution of participants (Wright & Stone, 1979). Later, the need for objective measurement, which is independent of the original scale and of the original group tested has been advocated by many researchers (Gulliksen, 1950; Loevinger, 1947) and which does not change with the times so that an accumulation of data for historical comparisons is accessible (Angoff, 1960).

To summarize, items using rating scales are requiring participants' opinions to which numbers are arbitrarily assigned to response categories to produce ordinal data. Therefore, ordinal data are not sufficiently interval to justify the arithmetical calculations used for obtaining means and variances (Wright, 1996). To satisfy the requirements for the analysis of ordinal data, transformed measures rather than raw data are needed for the analysis.

Problems in Developing Rating Scale Categorization

Determination of the well-functioning categorization has been an issue of interest to scale developers and many researchers have attempted to provide the optimal categorization in terms of the number of categories and the type of anchors (e.g., Guilford, 1954; Parducci & Wedell, 1986; Wedell, Parducci, & Lane, 1990). Since Likert introduced a five category agreement scale in 1932, there have been many arguments that eliminating the neutral category increases the quality of a scale, using more response categories rather than fewer categories is more advantageous, and a large number of response categories may confuse examinees (e.g., Guilford, 1954). Although the best method for constructing categorization has not been provided, it is commonly known that the way each rating scale is constructed is directly related to the way the variable is divided into categories, which affects the measurement quality of the data obtained from the scale (Clark & Schober, 1992; Linacre, 2002). Several features are required for an optimal categorization to elicit unambiguous responses. First, rating scales should reflect a common construct or trait in each question. Second, each category should have a respective boundary and those boundaries should be ordered based on the change of magnitudes of the trait (Guilford, 1954).

In the past, merely counting frequencies in each category has been the only method to investigate rating scale categorization. Some other statistics are also employed to test the scale and items, but none of these traditional statistics are appropriate for investigating the quality of categorization. For example, coefficient alpha and item-total correlation are used for determining homogeneity of the scale and items. However, it is still not clear whether the categories are systematically ordered because these statistics do not provide statistical information about the categorization being used. For this reason, only the number of items and the quality of each item

are overviewed based on the results of conventional statistics. Consequently, determining the number of response categories mostly relies on the researchers' knowledge or previous studies.

Even with great effort to develop an unambiguous rating scale, however, a test developer may fail to have participants react to a rating scale as designed (Roberts, 1994; Zhu, 2002). Applying only abstractive ideas and subjective knowledge to developing the optimal number of category has limitations in that no empirical test results are provided and the characteristics of the category function is not known.

Analyzing a Rating Scale

Traditionally, counting frequencies and transforming raw data have been employed to analyze a rating scale. Even though counting frequencies is somewhat simple and straightforward, applying this procedure is very limited in practice because analysis beyond each participant's ability is not available (Zhu, 1996). Transforming procedure, also known as mathematical models, can be classified in two ways: deterministic and probabilistic models. To obtain measurements from discrete observations, it is necessary to transform the observations from a rating scale to an interval or ratio scale before conducting an analysis.

Deterministic models

A deterministic model provides an exact prediction of an outcome based on assumptions such as no unsystematic or error variance in the model and all interpretable variation in the response is produced by the respondents and items. For example, a response pattern required by a Guttman scale shows perfect variation such as '1-1-1-1-1-1-0-0-0-0-0', where '1' indicates correctly answered items and '0' refers to incorrectly answered items.

However, Guttman model expectations for step-like development of sequential skills are unrealistically strict. In this model, each person must respond correctly to items in order of

difficulty until the difficulty of an item exceeds a person's ability. Then the person must respond incorrectly to all other items that are more difficult. Therefore, unexpected responses caused by participants guessing or fatigue commonly observed in practice, are not allowed in the model.

According to Andrich (1988), an error may exist between the prediction and the real value under the deterministic model, in which the error does not count because the values of interest are sufficiently great relative to the error, so the error would be ignored. In a deterministic procedure, participants are asked to rate each item in a number of categories previously defined. Based on the ratings, the values of the categories on an underlying continuum can be estimated and interval-scale values of the item can be determined (Zhu, 1996). Therefore, the deterministic model is used only for scaling items rather than individuals. The limitations of this model are that applying deterministic models is arbitrary because goodness-of-fit is not available in the model, and that deterministic models cannot account for variation in participants' responses to items due to the separate relation of each participant and each item to the underlying variable (Togerson, 1958). Furthermore, the deterministic models are likely to fit only a few types of data due to its empirically unrealistic expectations.

Probabilistic Models

In contrast to the deterministic approach, a probabilistic model assumes that there is a certain amount of unsystematic variance in the model. Therefore, the model may or may not account for all of the relevant causes of the outcome, and replications may produce differences in outcomes (Andrich, 1988). As a result, the outcomes are formalized in terms of probabilities. This probabilistic feature is more realistic in empirical practice. Indeed, the probabilistic model provides statistical criteria for goodness-of-fit of the model to the data which are advantageous for determining acceptance or rejection of a scaling hypothesis (Togerson, 1958).

The early work on probabilistic models mostly utilizes dichotomous data. Those models include the latent-linear model (Lazarsfeld & Henry, 1968), the latent distance model (Lazarsfeld & Henry, 1968), the normal ogive model (Lord, 1952), and logistic ogive models (Birnbaum, 1968). Lord's work on the normal ogive models in the 1950s was recognized as the origin of IRT. The normal ogive models were not easy to use due to their complex mathematical procedures such as integration. Later, Birnbaum introduced the logistic models and their statistical foundations as the form of the item characteristic curve, which is an explicit function of item and ability parameters. The logistic models were substituted for the normal ogive models so the normal ogive models are used mainly for historic reasons such as the relationship to classical test theory (Embretson & Reise, 2000; Zhu, 1990). All estimates in the logistic model essentially have the same interpretation as in the normal ogive model only if a scaling factor *D* (1.702) is added to the equation (Haley, 1952). The Rasch model, which is categorized to the logistic models, incorporates the attractive ordering features of the Guttman' scale model and complements them with a more realistic probabilistic, stochastic framework (Bond & Fox, 2001).

The Rasch Models

The Rasch model was developed under the probabilistic concepts. As a result of interest in modeling the relationship between a participant's underlying ability and response to a testing item, Rasch (1960/1980) constructed objective measures using dichotomously scored intelligence test scores to define item difficulty independent of participants being tested and person ability independent of test items being provided. Person ability is described as a position on an ability metric (i.e., latent continuum) and item difficulty is represented as the point on the ability metric at which the person has a fifty percent chance of answering the item correctly (Chang, 1985). Because the person ability and the item difficulty govern the probability of any

participant being successful on any particular item, the probability is a function of these two measures. In other word, the model expresses the probability of obtaining a correct answer as a function of the size of the difference between the ability of the person and the difficulty of the item. For example, a person has a higher probability of correctly answering an item that has lower difficulty than the ability of the person, and a lower probability of correctly answering an item with higher difficulty than the ability of the person. Although it is a simple concept, it is a critical feature of the Rasch model.

Even though the Rasch model was developed independently within the framework of probabilistic approach, the Rasch model is classified as an item response model in which the item characteristic curve is a one-parameter logistic function (Hambleton, 1985). Since the Rasch analysis was introduced, it has been extended to several models by researchers (e.g., Andersen, 1973; Andrich, 1978; Master, 1982; Master & Wright, 1984).

Logistic Models

The Rasch model is a simple stochastic model originally devised for dichotomously scored items. The Rasch model is categorized as a one-parameter logistic model of IRT (Zhu, 1990). In IRT an item characteristic curve (ICC) plays an important role. The ICC is the S-shaped curve indicating the relationship between the probability of correct response to an item and the ability scale (Baker, 1992). The ICC can be obtained from several mathematical models which are cumulative forms of the logistic function. One-, two-, and three-parameter logistic models are standard mathematical models and the most commonly known IRT models. While all three models are commonly utilizing dichotomous scores and employing an ability parameter and an item difficulty parameter, different numbers of parameter(s) are employed in each model.

Therefore, each model may result in different results with the same data. The mathematical forms of the three logistic models are defined as,

$$P_i(\theta) = \frac{e^{(\theta - b_i)}}{1 + e^{(\theta - b_i)}}, \qquad \text{(one-parameter model)} \qquad (2.1)$$

$$P_i(\theta) = \frac{e^{a_i(\theta - b_i)}}{1 + e^{a_i(\theta - b_i)}}, \qquad \text{(two-parameter model)} \qquad (2.2)$$

$$P_i(\theta) = c_i + (1 - c_i)\frac{e^{a_i(\theta - b_i)}}{1 + e^{a_i(\theta - b_i)}}. \qquad \text{(three-parameter model)} \qquad (2.3)$$

where $P_i(\theta)$ = the probability that a randomly selected examinee with ability θ will answer item *i* correctly,

a = the discrimination parameter of item *i*,

b = the difficulty parameter of item *i*,

c = the pseudo-guessing parameter (the probability of guessing), and

e = an exponent of the natural constant which equals 2.71828.

A one-parameter model involves an item parameter *b* denoting difficulty of a test item and an ability parameter θ indicating ability level of a participant. It is known as a one-parameter model because only one item parameter is designated in this model. A one-parameter model is similar to a three-parameter model if the pseudo-guessing parameter *c* is assumed to be minimal and the item discrimination *a* is assumed to be the same across all items in the test. Birnbaum proposed the two-parameter logistic model to substitute for the two-parameter normal ogive model (Hambleton, 1985). The difference between a three-parameter model and a two-parameter model is that in a two-parameter model there is no pseudo-guessing factor involved. The form of the ICC of this model is determined by the difficulty parameter *b* and the discrimination parameter *a*. The discrimination parameter dependent on the item information reflects the

steepness of the form of the ICC. The three-parameter logistic model differs from the two-parameter model in that the pseudo-guessing parameter is involved. The two-parameter logistic model can be obtained from the three-parameter logistic model mathematically if the pseudo-guessing parameter is assumed to be zero. The parameter *c* describes the goodness-of-fit of the low asymptote of the ICC and represents the probability of participants with low ability correctly answering an item by guessing. Among the three logistic models, the one-parameter logistic model is easier to apply and the model produces less estimation problems than other logistic models because a fewer number of item parameters is employed in the model.

Rasch Dichotomous Model

The Rasch dichotomous model is the original and simplest form of the Rasch family of models, which utilizes dichotomous scores such as correct and incorrect, yes and no, or present and absent. The Rasch dichotomous model is also classified as a one-parameter logistic model because the model predicts probabilities using an exponential form and includes one item parameter in describing items (Embretson & Hershberger, 1999). In a testing situation, score 1 is given to correct answer while 0 is assigned to incorrect response because there are only two response categories.

The Rasch dichotomous model uses the total score for estimating probabilities of response. Estimation of item difficulty and person ability starts from calculating the percentage of correct responses. For the estimation of person ability, the ratio of the percentage correct over the percentage incorrect calculated from each respondent is converted into odds. For example, when a person has completed four questions correct and six questions incorrect in a test with total of 10 questions, the ratio for the person is 40/60 and the natural log of the ratio is calculated. The value of ln(40/60) is assigned to the person for his or her ability estimate (-.4). For the

estimation of item difficulty, the same calculation is applied. These transformed values for items and persons are scaled on the same metric which is called logits. During the series of iteration for estimating parameter measures, the person ability estimates are constraint when item difficulties are estimated and vice versa. Therefore, estimations of difficulty parameter and ability parameter are statistically independent from testing items and samples used in the Rasch calibration. This invariance feature is the core of the Rasch analysis and also plays a important role in interpreting test results. Finally, the difference between the person parameter estimates (i.e., ability) and the item parameter estimates (i.e., difficulty) can be used to obtain the probabilities of success. This whole process of calculation transforms ordinal-level data into logits which have the same characteristics of interval data.

After person ability and item difficulty have been estimated, the probability of a person's success on certain item can be obtained by applying those estimated values to formula 2.1. Although the logistic parameter models presented in IRT books and Rasch measurement books are identical in their meanings, notation and symbols used for the models are not uniform. To prevent confusion from this, the notation presented by Wright and Masters (1982) will be used for all one-parameter logistic models hereafter. It can be defined as

$$P_{ni}(x_{ni} = 1 \mid \beta_n, \delta_i) = \frac{e^{(\beta n - \delta_i)}}{1 + e^{(\beta n - \delta_i)}}, \qquad (2.4)$$

where P_{ni} is the probability that person n responses correctly ($x = 1$) on item i with given person ability β_n and item difficulty δ_i. This equation therefore states that the probability P of person n getting a score x of 1 on a given item is a function of the difference between a person ability β_n and an item difficulty δ_i. For example, the probabilities for three cases where a person ability is higher than the item difficulty, person ability equals the item difficulty, and person ability is lower than the item difficulty can be obtained as follow.

$$P(x=1 \mid \beta(2), \delta(1)) = \frac{2.7183^{(2-1)}}{1+2.7183^{(2-1)}} = \frac{2.7183}{1+2.7183} = 0.73 \quad (2.5)$$

$$P(x=1 \mid \beta(2), \delta(2)) = \frac{2.7183^{(2-2)}}{1+2.7183^{(2-2)}} = \frac{1}{1+1} = 0.50 \quad (2.6)$$

$$P(x=1 \mid \beta(2), \delta(3)) = \frac{2.7183^{(2-3)}}{1+2.7183^{(2-3)}} = \frac{2.7183^{-1}}{1+2.7183^{-1}} = 0.27 \quad (2.7)$$

When an item with a difficulty estimate of 1 logit is given to a person with an ability estimate of 2 logits as in equation 2.5, the person has a 73% chance of successfully passing the item. If the estimated person ability equals the estimated item difficulty as in equation 2.6, the chance of successfully answering the item is 50%. If the same person is given an item with a difficulty estimate of 3 logits as in equation 2.7, the expected probability of correctly answering that item is 0.27, which is 27%. As mentioned earlier in this section, item difficulty estimates and person ability estimates are scaled on the same metric. Therefore, it is possible to compare both item difficulty and person ability on the same dimension. In general, when a person's ability estimate is greater than an item's difficulty estimate, the person has a more than 50% probability of success on the item. This is another advantage of the Rasch dichotomous model enhancing the interpretation of the results.

Rating Scale Model

The Rasch model has been extended to several one-parameter logistic models dealing with different types of scores (e.g., Andrich, 1978; Masters, 1982). Those models, called the Rasch family of models, include the rating scale model (Andrich, 1978), the partial credit model (Masters, 1982), and Poisson counts (Wright & Masters, 1982). The rating scale model (RSM) is an extended form of the Rasch dichotomous model in which items have more than two response

categories with order (e.g., Likert scales). An item with five response categories is modeled as having four thresholds. For example,

Strongly Disagree	→	Disagree	→	Neutral	→	Agree	→	Strongly Agree
0		1st		2nd		3rd		4th

if a participant chooses "Agree" for an item on an attitude questionnaire, the participant can be considered to have chosen "Disagree" over "Strongly Disagree", "Neutral" over "Disagree", and also "Agree" over "Neutral", but to have failed to choose "Strongly Agree" over "Agree". Therefore, completing the *k*th step can be thought of as choosing the *k*th alternative over the (*k*-1)th alternative in response to the item. Then the participant scores 3 on the item because the third step has been taken.

The RSM is distinguished from the Rasch dichotomous model by the threshold parameter τ_k. This new added parameter is a set of estimates for the certain number of thresholds that indicate the boundaries on the continuum between response categories (Andrich, 1978; Wright & Masters, 1982). The thresholds are estimated once for all items so, the set of threshold values are applied identically to all of the items on the scale. Therefore, the thresholds are the same across items in the same scale because it is assumed that items differ only in their locations, but not in their corresponding response categories, and the same set of alternatives is used with every item (Andersen, 1977; Andrich, 1978). The step difficulties are derived from the estimated item difficulties and thresholds. Each step difficulty is the sum of the item difficulty and each step threshold. Then the item difficulty is the mean of the step difficulties (Zhu, 1996). This expectation can be expressed by resolving each item difficulty from equation 2.4 into two components so $\delta_{ik} = \delta_i + \tau_k$, where δ_i is the location or scale value of item *i* on the variable

and τ_k is the location of the *k*th step in each item relative to that item's scale value. So, the RSM is defined as

$$P_{nik} = \frac{\exp[\beta_n - (\delta_i + \tau_k)]}{1 + \exp[\beta_n - (\delta_i + \tau_k)]} = \frac{e^{(\beta_n - \delta_i - \tau_k)}}{1 + e^{(\beta_n - \delta_i - \tau_k)}}, \quad (2.8)$$

where δ_i is the location or scale value of item *i*, and τ_k is a threshold parameter associated with transition between response categories *k*-1 and *k*. Each item threshold *k* has its own difficulty estimate τ. Each step (threshold) of rating scales is same as one dichotomous scale. Therefore, the estimate of each threshold's difficulty is modeled at which a person has a 50% chance of choosing one category over another. The thresholds for a set of rating scale items is described as the intersection of item probability curves for each response option.

To summarize, the RSM expresses the probability of any person choosing any given category on any item as a function of the agreeability of the person *n* and the likelihood of the entire item *i* at the given threshold *k* being chosen.

The Rasch Model Assessment

In this section, three sets of statistics provided by the Rasch analysis are discussed. The statistics include model-data fit statistics, category statistics, and reliability.

Model-Data Fit Statistics

The model-data fit statistics include two indices: Infit and Outfit (Wright & Masters, 1982). These statistics are used to identify particular items and participants having unacceptably large amounts of deviations from expectations. The Outfit statistic is simply an average of the standardized residual variance across both respondents and items. The Outfit statistic is more sensitive to unexpected responses such as outliers because the average is unweighted so it is not influenced by any other information. On the other hand, the Infit statistic denotes the weighted

mean square which has more emphasis on unexpected responses near a person's measure or an item's measure. Both Outfit and Infit statistics having values near 1 are considered satisfactory indications of model-data fit, and significantly larger or smaller values are considered misfit. A larger value indicates inconsistent performance, while a smaller value reflects too little variation.

The estimation of fit begins with the calculation of a response residual for each respondent when each item is encountered. Response residual is the deviation of the actual response from the Rasch model expectations. The Rasch analysis provides an expected value of the response x_{ni} for each person-item encounter in the data matrix. This expected value falls between 0 and the number of steps (thresholds), and is given by

$$E_{ni} = \sum_{k=0}^{m} kP_{nik} \ , \tag{2.9}$$

where P_{nik} is person *n*'s modeled probability of responding in category *k* to item i. When the expected value E_{ni} is subtracted from the observed response x_{ni}, a score residual y_{ni} is obtained as following

$$y_{ni} = x_{ni} - E_{ni} \ . \tag{2.10}$$

Score residuals can be calculated in this way for every cell of the data matrix. When data fit the RSM each score residual has an expected value of zero. To evaluate the score residual y_{ni} and its square y_{ni}^2 we compute the variance of x_{ni} by

$$W_{ni} = \sum_{k=0}^{m} (k - E_{ni})^2 P_{nik} \tag{2.11}$$

and its kurtosis by

$$C_{ni} = \sum_{k=0}^{m} (k - E_{ni})^4 P_{nik} \ . \tag{2.12}$$

The variance W_{ni} is largest when the person and item estimates are identical and decreases as person n and item i become further apart. As W_{ni} is also the variance of score residual y_{ni}, this score residual can be standardized by

$$z_{ni} = \frac{x_{ni} - E_{ni}}{W_{ni}^{1/2}} = \frac{y_{ni}}{\sqrt{W_{ni}}}. \quad (2.13)$$

These estimated values W_{ni}, C_{ni}, and z_{ni} are applied to the estimations of Outfit, Infit, and t-values.

Estimation of item fit. Because there are too many deviations, or residuals to examine in one matrix, the fit diagnosis typically is summarized in a fit statistic. One approach to summarizing the fit of an item to a measurement model is to square each of the standardized residuals for that item and average these squared residuals over the N persons. An unweighted mean square, called Outfit, can be calculated as

$$u_i = \frac{\sum_{n=1}^{N} Z_{ni}^2}{N}. \quad (2.14)$$

A disadvantage of statistic u_i is that it is rather sensitive to unexpected responses made by persons for whom item *i* is far too easy or far too difficult. When u_i is used, we may be led to reject an item as misfit because of just two or three unexpected responses made by persons for whom the item was quite inappropriate. An alternative is to weight the squared residuals so that responses made by persons for whom the item is inappropriate have less influence on the magnitude of the item fit statistic. A weighted mean square, called Infit, can be calculated as

$$v_i = \frac{\sum_{n=1}^{N} Z_{ni}^2 W_{ni}}{\sum_{n=1}^{N} W_{ni}} = \frac{\sum_{n=1}^{N} y_{ni}^2}{\sum_{n=1}^{N} W_{ni}}. \quad (2.15)$$

In this statistic each squared residual z_{ni}^2 is weighted by its variance W_{ni}. Since the variance is smallest for persons furthest from item *i*, the contribution to v_i of their responses is reduced. When data fit the model, the statistic v_i has an approximately mean square distribution with expectation one. The variance of item Infit can be calculated by

$$q_i^2 = \frac{\sum_n^N (C_{ni} - W_{ni}^2)}{(\sum_n^N W_{ni})^2}. \quad (2.16)$$

To compare values of v_i for different items it is convenient to standardize these mean squares to the statistic (item fit *t*-value).

$$t_i = (v_i^{1/3} - 1)(3/q_i) + (q_i/3) \quad (2.17)$$

which, when data fit the model, has a mean near zero and a standard deviation near one.

Estimation of Person Fit

Estimating procedure for person fit is identical with that of item fit except that residuals are accumulated over items for each person to obtain a statistic. Therefore, this statistic summarizes the fit of a person to the model. Infit statistic (i.e., the weighted mean square) can be calculated as

$$v_n = \frac{\sum_{i=1}^L Z_{ni}^2 W_{ni}}{\sum_{i=1}^L W_{ni}} = \frac{\sum_{i=1}^L y_{ni}^2}{\sum_{i=1}^L W_{ni}}. \quad (2.18)$$

When data fit the model, the statistic v_n has an approximately mean square distribution with expectation one. The variance of person Infit can be calculated by

$$q_n^2 = \frac{\sum_i^L (C_{ni} - W_{ni}^2)}{(\sum_i^L W_{ni})^2}. \quad (2.19)$$

To compare values of v_n for different persons, the weighted mean square can be standardized to a statistic (person fit *t*-value) by

$$t_n = (v_n^{1/3} - 1)(3/q_n) + (q_n/3). \quad (2.20)$$

When data fit the model, t_n has a mean near zero (expectation) and a variance near one.

Person fit statistics parallel the corresponding item fit statistics exactly. The only difference is that now squared residuals are summed over items for a person rather than over persons for an item. Item fit statistics play an important role in the construction and calibration of an instrument. Person fit statistics are useful for assessing the validity of measures made with instruments which have already been established. In general, more emphasis is placed on Infit values than on Outfit values in identifying misfitting persons or items (Bond & Fox, 2001).

Category Statistics

It is important to investigate whether each scale category is functioning as intended in ordinal observations. The Rasch software, WINSTEPS (Linacre, 2004b), provides several sets of statistics indicating the characteristics of categorization. Even though each statistic is expressed in different ways, they provide the same information in terms of the hierarchical order of categories and the magnitude of distance between categories. These statistics are usually used in combination for detecting any disordered categorization, defining problematic categories for collapsing, and determining the optimal categorization.

Average Measure

Average measure is the empirical average of the measures (i.e., ability of the participants) observed in a particular category across all items. The average measure is expected to increase with category value because more of the rating scale is modeled to reflect more of the variable being measured (Linacre & Wright, 1999). If average measures are not ordered, the specification that better performers should produce higher ratings is violated.

Step calibration

The Rasch model detects the threshold structure of the Likert-type scale in the data set rather than presuming the size of the step necessary to move across each threshold. Then the model estimates a single set of threshold values that apply identically to all of the items in the scale. In addition to the monotonicity of average measures, step calibration provides useful information concerning rating scale characteristics. Step calibration is the difficulty estimated for choosing one response category over the prior response. When the characteristics of categorization are investigated based on step calibrations, two aspects should be considered. First, like the average measures, step calibrations are expected to increase monotonically. Second, the magnitudes of the distances between the threshold estimates in logits should be greater than 1.4 (1.0 for a five response categorization) and smaller than 5.0 because the respective distances between step calibrations indicate each step's distinct position on the variable (Linacre, 2002; Linacre & Wright, 1999).

Category fit statistic

The categories of a scale can be used arbitrarily even with ordered average measures. Category fit statistic is another criterion for assessing the quality of rating scales. Category fit provides Infit which is the average of the Infit mean squares associated with the responses in each category and Outfit which is the average of the Outfit mean squares associated with the

responses in each category. For both Infit and Outfit, expected values for all categories are 1.0 and range from 0 to infinity. High Infit indicates that a certain category is chosen when adjacent categories are expected to be chosen whereas high Outfit mean square indicates that a certain category is chosen when distant categories are expected to be chosen (Linacre & Wright, 1999). Values less than 1.0 indicate overly predictable category use for both fit statistics.

In general, Outfit mean squares which are sensitive to outliers are mainly used to investigate category fit. Outfit mean squares values greater than 2.0 indicate more misinformation than information (e.g., the value 2.0 indicates half information and half misinformation). If a category has an Outfit value over 2.0, under the assumption of plausible linguistic aspects of category definitions, further empirical investigation is required so collapsing with adjacent categories is recommended.

Reliability Statistics

Items must be well separated and defined to identify the direction and magnitude of a variable because the variable is measured with test or questionnaire items and expressed in terms of the scores from the scale (Wright & Masters, 1982). In addition, it is also important to define how well individual differences are identified with a test or questionnaire. In this regard, the Rasch model provides two useful indices describing the separation of items on a variable and the separation of persons on a scale, respectively.

Item separation index G_I is an estimate of how well the scale separates test items. The value of the index is estimated as the adjusted item standard deviation SA_I divided by the average measurement error SE_I.

$$G_I = \frac{SA_I}{SE_I}. \qquad (2.21)$$

The adjusted item standard deviation is simply the root of the adjusted item variance SA_I^2 calculated by subtracting the mean square item calibration error MSE_I from the observed item variance SD_I^2.

$$SA_I^2 = SD_I^2 - MSE_I . \quad (2.22)$$

The observed item variance SD_I^2 is the variance among calibrations of item difficulty d_i. The mean square item calibration error MSE_I can be obtained by dividing the total error variance of the items by the total number of items.

$$MSE_I = \frac{\sum_{i=1}^{L} s_i^2}{L} . \quad (2.23)$$

Then the mean square item calibration error is used to obtain an average calibration error.

$$SE_I = \sqrt{(MSE_I)} . \quad (2.24)$$

The adjusted item variance SA_I^2 can be used to estimate the item separation reliability R_I which indicates the replicability of item difficulty across persons.

$$R_I = \frac{SA_I^2}{SD_I^2} = 1 - \frac{MSE_I}{SD_I^2} = \frac{G_I^2}{(1+G_I^2)} . \quad (2.25)$$

The differences between the item separation index and the item separation reliability are that the latter does not include the measurement error which is not accounted for by the Rasch model, and that the latter ranges from ranges from 0 to 1.

Person separation index G_P is an estimate of how well the scale identifies individual differences. The value of the index is estimated as the adjusted person standard deviation SA_P divided by the average measurement error SE_P.

$$G_P = \frac{SA_P}{SE_P}. \tag{2.26}$$

The adjusted person standard deviation is simply the root of the adjusted person variance SA_P^2 calculated by subtracting the mean square person calibration error MSE_P from the observed person variance SD_P^2.

$$SA_P^2 = SD_P^2 - MSE_P \tag{2.27}$$

The observed person variance SD_P^2 is the variance among calibrations of person ability b_n. The mean square person calibration error MSE_P can be obtained by dividing total error variance of persons by the sample size.

$$MSE_P = \frac{\sum_{n=1}^{N} s_n^2}{N} \tag{2.28}$$

Then the mean square person calibration error is used to obtain an average calibration error.

$$SE_P = \sqrt{(MSE_P)} \tag{2.29}$$

The adjusted person variance SA_P^2 can be used to estimate the person separation reliability R_P which indicates the replicability of person placement across other items measuring the same construct (Bond & Fox, 2001).

$$R_P = \frac{SA_P^2}{SD_P^2} = 1 - \frac{MSE_P}{SD_P^2} = \frac{G_P^2}{(1+G_P^2)}. \tag{2.30}$$

As in the item separation reliability, the measurement error is not included in the equation and the value of the reliability ranges from 0 to 1.

For item and person separation indices, the greater the value, the better the separation. For item and person reliabilities, a value close to 1 is considered good reliability because the

value indicates the percentage of observed response variance that is reproducible. When both item and person separation indices are used to determine the optimal categorization, the greater the separation, the better the categorization because the item will be better separated and the participants' differences will be better distinguished.

The Rasch Calibration

In general, the term calibration is defined as the process of defining a measurement system for an instrument, which provides a frame of reference for interpreting test results. In the Rasch analysis, the term calibration has been used in various ways. According to Chang's (1985) definition, it can be categorized in two ways. In its narrow sense, calibration refers to the part of or whole processes of estimation of item difficulty parameter values and their standard errors, placement of items according to their difficulty estimates on a common scale, and estimation of values for both difficulty and ability parameters. In its broad sense, evaluation of fit to the model is added to the estimation of difficulty and ability parameters. In current studies of the Rasch models, the term calibration is commonly used in its broad sense that refers to the process of converting raw scores to logits to determine the values of item difficulty and person ability in a metric for the underlying latent trait in addition to the evaluation of models based on various fit statistics (e.g., Hand & Larkin, 2001; Kulinna & Zhu, 2001; Looney & Rimmer, 2003; Ludlow & Haley, 1995; Smith, Jr., & Dupeyrat, 2001; Zhu et al., 2001).

The Rasch calibration, which is categorized as a response-centered approach, is known to provide several advantages over traditional calibration techniques. First, estimations of difficulty parameter and ability parameter are statistically independent from testing items and samples of participants employed in the Rasch calibration. This invariance feature is very important in interpreting testing results because participants' abilities should remain the same regardless of

which testing items are used, and estimates of the difficulty of items are independent of the particular persons and other items included in the calibration. Second, items and persons are located respectively along a common scale based on their estimated values. The common scale, logit, is a ratio scale expressed in probability. Therefore, any difference between examinees and items on a scale will always have the same stochastic consequence. Subsequently, both parameters can be interpreted simultaneously within a single framework. Third, after the Rasch calibration, total scores or subscale scores from ordinal data can be used for additional analyses because measures provided by the calibration are additive.

The characteristics of the Rasch calibration described in this section provide a solution to the practical measurement problems in analyzing ordinal data using classical test techniques or subject-centered approaches. Therefore, applying the Rasch calibration is beneficial and essential to interpreting rating scales.

Optimal Categorization

It is known that categorization must be ordered according to the magnitude of the trait and have well-defined boundaries because these features affect the measurement qualities (Andrich, 1997; Guilford, 1954). These features of categorization are influenced by the amount of misinformation in a rating scale. Misinformation or noise in rating scales usually results from the disagreement between participants' perception and the scale developers' intention for the rating scale, or from the absence of generalized and standardized perception of a rating scale among participants. That is, although scale developers increase the number of response alternatives to provide participants with more possible responses to choose, participants may fail to react to a rating scale as the scale developers intended due to the divergent frames of reference (Roberts, 1994). However, such information, empirically and mathematically, had not been

provided with conventional statistics until the Rasch analysis was introduced. Although the Rasch model was developed for the purpose of objective measurement, the Rasch analysis can also be used as a post-hoc approach that provides helpful information for testing categorization function.

The Rating Scale Diagnostics

According to Bond and Fox (2001), several important aspects of categorization function can be investigated through the Rasch analysis. They suggested that a well-functioning category rating scale should have enough data (i.e., observed frequencies) in each category to provide stable estimates for threshold values, hierarchically ordered thresholds, and sufficient category fit to the model. Even though category function may not be observed in the raw data, these aspects can be diagnosed through investigating category frequencies, average measures in logits, threshold estimates, probability curves, and category fit after the initial calibration with the original categorization.

Inspecting category frequencies for each response option is the first thing done when examining category function (Andrich, 1996; Linacre, 1995, 2002). Category frequencies indicate the total number of participants who chose a response category across all items of a questionnaire. These category frequencies provide information related to observation distribution. Irregularity such as highly skewed distributions indicates aberrant category usage whereas a uniform distribution of observations across categories is optimal for step calibration (Linacre, 2002). In addition, frequency of each category is used for detecting low observations affecting stable estimation of thresholds. Because each threshold is estimated from the log-ratio of the frequency of its adjacent categories, the estimated scale structure can be highly affected by even one observation change when category frequency is less than 10 observations (Linacre, 2002).

Second, the monotonic increments of average measures can be examined for category function. Average measures indicate the average of the ability estimates for all participants in a particular category. Because only one set of threshold estimates are estimated for all items in a questionnaire, the average measure of a certain category can be interpreted as the average ability estimate in logits for participants who chose the category on any item in the questionnaire. Therefore, observations in higher categories must be produced by higher measures. In other words, average measures reflect the pattern of monotonic increment when participants with lower ability or attitude choose the lower categories and participants with higher ability or attitude choose the higher categories. Third, thresholds are the difficulties estimated for choosing one response category over another. Like the average measures, thresholds should increase monotonically. If thresholds do not increase monotonically across the rating scale, categories are considered disordered which reflects the low probability of observing certain categories and which decreases the interpretability of the resulting measures. Thresholds can be inspected based on either the threshold estimates or the probability curves. Linacre (2002) suggested that thresholds for a rating scale with five response options should advance by at least 1.0 logits to show distinction between categories, but not more than 5.0 logits to avoid large gaps, called 'dead zone', in the middle of the category in which a measurement loses its precision. When inspecting category curves, each category should have a distinct peak in the probability curve graph. Because threshold estimates correspond to the intersection of adjacent category curves, a category without a distinct peak cannot be the most probable response category for some portion of the measured variable which results in disordered thresholds. Finally, investigating category fit expressed in terms of Outfit mean square is useful for assessing the quality of category

function. An Outfit mean square value greater than 2.0 indicate that there is more unexplained information than explained information in the observation of the category.

Even though these diagnostics provide the same information in different ways, it is recommended to use the diagnostics in combination to detect problems in category function. When any violation is found, collapsing adjacent categories is recommended to increase the reliability and validity of the measure.

Collapsing Categories

The purposes of collapsing categories are to minimize misinformation across categories, to improve variable clarity, and to derive the optimal categorization. If problems such as infrequently used categories, category disorder, and poorly defined boundaries are found in categorization, it is recommended to combine the problematic response category with adjacent category (Bond & Fox, 2001; Linacre, 2002). Therefore, revising the rating scale starts from deriving new combinations from the original categorization.

There are two ways to collapse categories although both methods employ the identical Rasch diagnostic procedures. The first method is to collapse only categories having category function problems up or down with adjacent category. This method is recommended when it is obvious that deriving only a limited number of combinations leads to an optimal categorization. Another method, called mechanical way in Zhu and Kang's (1998) study, is that all possible combinations are derived from the original categorization. For example, Zhu and Kang (1998) recombined the original five adjacent categories into two, three, and four categories in their Rasch analysis using a self-efficacy scale. All 15 categorizations including fourteen sets of derived categorizations and the original categorization were analyzed individually. Even though this mechanical way requires repeating the same protocol until all derived data sets are analyzed,

all possible combinations can be compared. The mechanical way is preferred when researchers are uncertain of the exact number of response categories to be collapsed into because any features or characteristics of the optimal categorization cannot be observed from the raw data.

Once the collapsing formats are determined, the Rasch analysis is applied to all the data sets recombined. Each categorization is examined and compared based on category information and statistics provided by the Rasch analysis. First, model-data fit statistics are examined to investigate how many items and persons are misfit in terms of Infit and Outfit, and to determine whether a categorization is acceptable for further comparison and investigation. Second, category average measures and threshold estimates are examined to inspect the order of each categorization. Finally, the categorizations with hierarchical order are compared based on item and person separation indices. From the final comparisons, the categorization with the greatest separation values is chosen for the optimal categorization.

Measurement of Body Image

The importance of understanding body image has increased because it is known that dissatisfaction with body image is significantly related to the development of eating disorders such as anorexia nervosa and bulimia nervosa (Brown, Cash, & Lewis, 1989; Thompson, 1996; Williamson, Cubic, & Gleaves, 1993) and perceived body image influences exercise motives and adherence (Ingledew & Sullivan, 2002). In this regard, body image has been studied in terms of body size and appearance, dissatisfaction, physique anxiety, and social pressure. Instruments and techniques have been recently developed or revised to measure body image constructs.

Due to the implicit nature of body image, the term body image has been used to describe a wide range of body-related constructs but some researchers have used the term to indicate a very specific concept of body. Even though there is still disagreement in defining body image,

Rowe (1996) categorized instruments measuring body image into two types. Instruments in the first category have been devised for measuring size-perception accuracy which is related to the ability to estimate the size of one's own body in a whole or part (e.g., Askevold, 1975; Freeman, Thomas, Solyom, & Hunter, 1984; Ruff & Barrios, 1986; Slade & Russell, 1973). On the other hand, instruments in the second category have been developed for measuring cognitive-affective aspect of body image. Different from size-perception accuracy measurement, participants' attitudes toward the body and physical appearance are of interest in measurement of cognitive-affective aspect (e.g., Cash, Winstead, & Janda, 1986; Garner, Olmstead, & Polivy, 1983; Kurtz, 1969). In measuring participants' attitudes toward body image, which is the assessment of the cognitive-affective dimensions of body image, the most common type of instruments has been questionnaires (Baumgartner et al., 2003; Rowe, 1996).

Currently, it is common for researchers to use a part of a previous instrument or several different instruments in combination to measure an expected trait such as eating disorders, social pressure, and exercise adherence (e.g., Hausenblas & Fallon, 2002; Ingledew & Sullivan, 2002; Stice, Maxfield, & Wells, 2003). For example, Hausenblas and Fallon (2002) used a multitude of instruments in the investigation of the relationship among body image, exercise behavior, and exercise dependence symptoms in physically active individuals. In their study, a subscale (i.e., Drive for Thinness) of the Eating Disorder Inventory-2 (Garner, 1991), the Leisure-Time Exercise Questionnaire (Godin, Jobin, & Bouillon, 1986), selected items from the Multidimensional Body-Self Relations Questionnaire (Cash, 1990), the Social Physique Anxiety Scale (Martin, Rejeski, Leary, McAuley, & Bain, 1997), and 21 revised items from the DSM-IV (Hausenblas & Symons Downs, 2001) were employed to measure weight preoccupation, the

frequency of exercise, the subjective component of body image, physique anxiety, and exercise dependency, respectively.

Characteristics of Body Self-Image Questionnaire

Several issues concerning instruments measuring body image have been identified such as a theoretical foundation is insufficient to develop body image measurement instruments, the concept of body image being measured is not declared explicitly, and existing instruments lack of psychometrically sound methods and construct validity evidence (Baumgartner et al., 2003; Rowe, 1996; Thompson, 1996). For example, no conceptual explanation or any empirical evidence is provided either for the original version or the revised formats of the Body Self-Relations Questionnaire (Cash, 1990) although the original and revised instruments have been widely used. Consequently, the instruments produce ambiguity and doubt in the interpretation of research results.

Rowe (1996) developed a questionnaire because of the need for an explicit foundation of body image and empirical evidence of construct validity. In his study, the nature of the body image construct was investigated and the BSIQ was developed and validated to measure body image in college students. Data were collected through four stages. Responses to open-ended questions administered in the first pilot stage were used to develop statements for the questionnaire. In the second and third pilot stages, exploratory factor analyses and item-subscale correlations were used to guide revisions to the questionnaire. The final stage involved the collection of evidence to support the construct validity of the questionnaire. In the final stage, observations from 1024 undergraduate students were randomly divided into two subsamples. Confirmatory factor analysis (CFA) was applied to a subsample (i.e., calibration sample) for calibration in which the measurement model underlying the questionnaire was modified. The

result of the CFA supported acceptable fit for a nine-factor model with 39 items. The model was also cross-validated with the other subsample (i.e., validation sample) by imposing the parameter values from the calibration sample on the validation sample data. After the model was generated, *t*-tests were conducted to provide discriminant evidence of construct validity. Discriminant evidence of construct validity was obtained by comparing the females in the final sample to additionally collected samples; female students with eating disorders and female students who were dancers. Mean scores of the students with eating disorders indicated that they evaluated their overall appearance, health/fitness level, and fatness more negatively, and expressed more negative feelings about their bodies than the students in the final sample. On the other hand, the student dancers' mean scores indicated that they evaluated their overall appearance, fatness level, and health/fitness level more positively, and expressed less negative feelings about their bodies than the students in the final sample.

The Rasch Analysis for Measurement Problems of Body Image Instruments

Most instruments for the cognitive-affective domain of body image have been questionnaires and Likert-type response options have been employed for those instruments. As pointed out by Rowe (1996), many instruments have failed to provide psychometric evidence despite the instruments are commonly used in practice. The BSIQ was developed with the researcher making an effort to eliminate the shortcomings of previous body image questionnaires such as insufficient understanding of body image constructs and the lack of reliability and validity evidence. Although providing the psychometric evidence may seem to reduce or eliminate the shortcomings and to improve the quality of the instrument, some fundamental measurement issues arise because ordinal data from the Likert-type scale were directly used for analyses. Ordinal data are not sufficiently interval to justify the arithmetical calculations

employed by t-tests and factor analysis (Wright, 1996). Additionally, categorization affects the quality of an instrument that is directly related to the distribution of the data. However, it is not known whether the five-point category options functioned as intended because no statistical or empirical evidence is provided from the conventional procedures used in the study.

Applying the Rasch model to the analysis of rating scales have several advantages in solving those measurement problems. The Rasch calibration transforms the ordinal data, more specifically both item difficulty and person ability (i.e., body image satisfaction) into logits which have the same characteristics of interval data. Therefore, not only calculating total scores but also comparing both facets simultaneously on the same metric is possible, which were not possible with the conventional statistics in Rowe's (1996) study. This transformation also enables researchers to do further statistical analysis such as comparison of two diverse groups for construct validity without linearity concerns. Another advantage of the Rasch analysis is that optimal categorization can be determined for the BSIQ in an empirical way because it provides information for testing categorization function. Because the Rasch analysis is used for detecting optimal categorization as a data-based and post-hoc approach, it generates all possible combinations of categorization from the original data instead of requiring that additional data with several sets of predetermined categorization be collected.

CHAPTER 3

PROCEDURES

The primary purpose of this study was to calibrate the BSIQ (Rowe, 1996) to construct an objective and additive scale by transforming the raw data from an ordinal scale into logits using the Rasch analysis. The secondary purpose was to determine the optimal categorization for each subscale of the BSIQ. Procedures included (a) calibrating the BSIQ initially to determine the optimal categorization, (b) constructing items with acceptable fit statistics in each subscale (i.e., factor), (c) validating the model using a smaller sample, and (e) describing item difficulty and person ability (i.e., body image satisfaction) on the same continuum. In addition, groups formed based on body mass index (BMI) were examined for differences in logits as evidence of construct validity of the questionnaire. Procedures and descriptions of the data analysis are provided in Table 1.

Data and Instrument

Data

In this study, data from a previous body image study were used with permission from the researcher (Rowe, 1996). Data were collected from male and female undergraduate students who were participating in physical education activity classes at the University of Georgia. Rowe (1996) intended to sample from various types of classes because personal status such as previous fitness experience and attitude might be related to the choice of class.

In the present study, the total sample, which included 1021 participants, was used for the Rasch calibration. Additionally, a smaller sample, the validation sample, was generated randomly from the total sample for confirming the revised categorization and the retained items and for providing evidence of construct validity. Demographic information for the total sample and the validation sample are presented in Table 2.

The Body Self-Image Questionnaire

The questionnaire used in the present study was originally developed for measuring body self-image in undergraduate students (Rowe, 1996). In Rowe's study, a total of 56 items were initially administered to the participants and 39 items under nine factors were retained with acceptable fit based on factor analyses. A Likert-type five-point scale (Not at all true of myself = 1, Slightly true of myself = 2, About halfway true of myself = 3, Mostly true of myself = 4, and Completely true of myself = 5) was used for all items. Therefore, the BSIQ consists of 39 items with a Likert-type five-point scale under nine factors including overall appearance evaluation, fatness evaluation, health/fitness evaluation, negative affect, health/fitness influence, social dependence, investment in ideals, attention to grooming, and height dissatisfaction. Because the BSIQ was developed to measure the multidimensional constructs of body image, it was not intended by Rowe to obtain a total score from the questionnaire, rather the subscale scores from each factor were of interest in investigating university students' body self-image related constructs. Therefore, the nine subscales using the factors of the BSIQ were calibrated separately for the Rasch analysis.

The procedures in detail for developing the BSIQ are described in the related research. The thirty-nine items and the response format for the BSIQ are presented in Appendix A and the nine factors with related items are provided in Appendix B.

Data Analyses

The RSM was employed in the present study and the model was applied to the BSIQ data for calibrating ordinal data, investigating category function, determining optimal categorization, and constructing items for each subscale. The validation sample was analyzed to conduct cross-validation and construct validity studies.

Calibration

Nine subscales of the BSIQ, overall appearance evaluation (OAE), fatness evaluation (FE), attention to grooming (AG), health/ fitness evaluation (HFE), health/ fitness influence (HFI), social dependence (SD), height dissatisfaction (HD), negative affect (NA), and investment in ideal (II), were separately calibrated using the RSM. For the initial calibration, no modification was made in the categorization and the number of items for each subscale.

Category Function

The Rasch analysis was applied to the BSIQ to determine whether the Likert-type five-point scale was optimal or some other response format was more appropriate for the data. Since the best categorization would not be observed in the raw data, category function from the initial calibration was examined to determine whether the Likert-type five-point scale was ordered with increasing or decreasing numerical trait.

Linacre (2002) introduced useful guidelines for optimizing rating scale category effectiveness. The guidelines were used in the present study for investigating category function. The description of the guidelines used in the present study is summarized in Table 3.

For a categorization with any violation according to the guidelines, a collapsing process was applied to combine the original five categories into three or four categories in order to improve the overall measurement quality. For example, Zhu, Timm, and Ainsworth (2001)

calibrated a 23-item exercise barrier instrument with the Rasch analysis and they collapsed the original five categories (i.e., Very Often, Often, Sometimes, Rarely, and Never) into three and four categories in their study. The collapsing combinations were 11123, 11233, 11223, 12223, 12233, and 12333 for three categories, and 11234, 12234, 12334, and 12344 for four categories. For example, the collapsing combination 11123 is combining the first three categories to become a score of 1, the fourth category becomes a score of 2, and the fifth category becomes a score of 3. However, it should be cautioned that information may be lost if a positive response category and a negative response category are combined into a category. For example, Zhu and colleagues combined the Often, Sometimes, and Rarely categories into a new category in a combination 12223. While this combining may increase fit statistics, it may be meaningless in terms of interpreting the respondents' perceived construct on the categorization.

Therefore, in the present study, only the categories that violated category count, hierarchal order, and the step calibration advance were combined with adjacent categories as suggested by Linacre (2002) instead of trying to combine based on all possible combinations. First, in each subscales, categorization with acceptable Outfit mean squares (< 2.0), category counts more than 10 responses in each category, hierarchically ordered average measures and step calibrations, and step calibration advances equal or larger than 1.0 logit and smaller than 5.0 logits were retained as appropriate for corresponding subscales.

Second, categories with any violation of the criteria described in Table 3 were combined with adjacent categories (i.e., *k*-1 category) then the data with the collapsed categorization were recalibrated. When two or more collapsing combinations existed in a subscale, the combination with the category fit statistics closer to 1.0 mean square, and with better item and person separation statistics was retained as the optimal categorization for the subscale. Item and person

separation statistics provide information concerning how well a scale separates testing items and participants, respectively (Wright & Masters, 1982). For item and person separation statistics, the larger the value of the indices, the better the separation.

Misfitting Item Deletion

Item fit statistics were investigated to determine which items to delete for each subscale. Acceptable ranges for both Infit and Outfit mean squares were set at $.60 \leq \text{fit} \leq 1.40$ which was suggested for rating scales with Likert-type responses by Bond and Fox (2001). After the deletion of misfitting item(s) from a subscale, the data with the retained items were recalibrated to investigate item fits and to obtain parameter estimates.

Cross-Validation

The modification in the categorization and the structure of a rating scale may be sample dependent. The RSM was applied to the data of the validation sample for confirming that the categorization retained or revised for each subscale and the retained items in each subscale were acceptable. The validation sample was generated from the total sample ($N = 1021$) by selecting 510 participants randomly using the SPSS program.

First, the category function for each subscale was examined based on category frequency, average measure, step calibration, and Outfit statistic with the same criteria used in the collapsing process for the total sample. Then, the pattern of categorization for the validation sample was compared to the pattern of categorization for the total sample. Second, to investigate the stability of the Rasch estimation for item difficulty, the hierarchical order of items for the total and validation samples were compared for each subscale.

Construct Validity

Body mass index (BMI) has been widely used to estimate body composition in field settings (Baumgartner et al., 2003). Based on the research literature, the degrees of body dissatisfaction and social physique anxiety are influenced by the level of BMI of individuals. Even though BMI has a high predictive error especially when physically active males with high lean body mass are measured, many researchers have suggested that BMI is significantly associated with body dissatisfaction (Ingledew & Sullivan, 2002; Pietrobelli, Faith, Allison, Gallagher, Chiumello, & Heymsfield, 1998). Hausenblas and Fallon (2002) also reported that BMI was the positive predictor of body dissatisfaction and social physique anxiety for females. According to American College of Sports Medicine's (ACSM) guidelines, obesity-related health problems increase beyond a BMI of 25 for most people (ACSM, 2000). World Health Organization defines a BMI between 18.5 and 24.9 as normal, 25 to 29.9 as overweight, and 30 or greater as obesity (Baumgartner et al., 2003).

To test if the BSIQ measures reflect a related abstract trait (i.e., body image satisfaction or dissatisfaction) which is influenced by BMI after calibration and revision, a construct validity approach was employed with a statistical test of mean difference among groups. The validation sample was divided into three groups based on each participant's BMI; underweight (< 18.5), normal (18.5~24.9), and overweight (25 or higher). Descriptives for the three groups are presented in Table 4. The group mean differences of person measures in logits generated from the Rasch calibration in each subscale were examined. One-way analysis of variance (ANOVA) with alpha level of .05 was used for investigating group mean difference. Consequently, the group means were contrasted using the *t*-test for two independent groups to examine which groups significantly differenced. To reduce the cumulative type I error, the alpha level of .05 was

divided by the number of contrasts for each subscale (Keppel, 1991). The rounded alpha level of .02 was used for the contrasts.

Table 1

Order of the Data Analysis

Analysis	Sample size	Description and criteria
Initial calibration for each subscale	1021	Each subscale data of the BSIQ was calibrated using the RSM.
Determining the optimal categorization	1021	Collapsing categories was applied when one or more violations described in the guidelines (Linacre, 2002) were found in category function for subscales.
Detecting and deleting misfitting items	1021	Items with Infit and Outfit mean squares smaller than .60 and larger than 1.40 were considered misfit and were deleted from subscales.
Parameter estimation	1021	Item and person measures were estimated from the total sample calibration with the optimal categorization and retained items of the BSIQ.
Cross-validation	510	The patterns of category function and item construct for each subscale using the validation sample were investigated to test the stability of parameter estimation across samples.
Construct validity	510	Three BMI-based groups were examined for differences in the body self-image satisfaction and dissatisfaction as evidence of construct validity of the BSIQ.

Note. BSIQ: Body Self-Image Questionnaire. BMI: Body Mass Index. RSM: Rating Scale Model

Table 2

Characteristics of the Participants

Characteristic	Total Sample (N = 1021)	Validation Sample (n = 510)
Gender		
Male	431 (42.2%)	211 (41.4%)
Female	590 (57.8%)	299 (58.6%)
Grade		
Freshman	209 (20.5%)	93 (18.2%)
Sophomore	473 (46.3%)	250 (49.0%)
Junior	237 (23.2%)	123 (24.1%)
Senior	101 (9.9%)	43 (8.4%)
Ethnic		
African-American	71 (7.0%)	32 (6.3%)
Asia-American	48 (4.7%)	22 (4.3%)
Caucasian	845 (82.5%)	427 (83.7%)
Other ethnic	46 (4.5%)	21 (4.1%)
Descriptives		
Mean age (*SD*)	19.91 (1.42)	19.88 (1.37)
Mean height (*SD*)	67.49 (4.16)	67.47 (4.05)
Mean weight (*SD*)	147.74 (32.33)	147.88 (31.98)
Mean BMI (*SD*)	22.69 (3.97)	22.74 (3.99)

Note. BMI: Body Mass Index. Validation sample was randomly extracted from the total sample. Height was in inches. Weight was in pounds.

Table 3

Guidelines for Optimizing Category Effectiveness

Guideline	Description
At least 10 observations in each category	Lower observation may result in imprecise estimate of step calibration because it is estimated from the log-ratio of the frequency of its adjacent categories.
Hierarchically ordered average measure	Disorder in average measure may result when a lower category is dominantly chosen by participants with higher measures or a higher category is chosen by participants with lower measures.
Outfit mean square less than 2.0	If Outfit mean square for a category is larger than 2.0, the categorization is unproductive for construction of measurement and distorts and degrades the measurement system.
Hierarchically ordered step calibration	Disorder in step calibration may result if a lower category is chosen by participants with higher measures and vice versa.
The advance between step calibrations ≥ 1.0 logit	For a five category rating scale, advances of at least 1.0 logits between step calibrations are needed in order for that scale to be equivalent to four separate dichotomies, and to have wider substantive meaning.
The advance between step calibrations ≤ 5.0 logits	If the step calibrations are more than 5 logits apart, the scale provides less information about the participants.

Table 4

Characteristics of the Three Groups Based on Body Mass Index (BMI) in the Validation Sample

	Underweight (*n* = 36)	Normal (*n* = 365)	Overweight (*n* = 102)
Male	3	143	60
Female	33	222	42
Age	19.62 (.74)	19.86 (1.36)	20.07 (1.56)
Height	65.92 (2.87)	67.53 (3.92)	67.79 (4.75)
Weight	107.25 (13.65)	141.10 (21.66)	186.68 (32.57)
BMI	17.30 (1.37)	21.65 (1.75)	28.55 (4.32)

Note. BMI: body mass index. Missing cases = 7. Values in parentheses are standard deviation. Height was in inches. Weight was in pounds.

CHAPTER 4

RESULTS AND DISCUSSION

The BSIQ data were analyzed with the RSM. The category function and item structure for each subscale were investigated. Subsequently, the RSM was applied to the validation sample to investigate the model sensitivity to sample size change and to confirm the revised categorization and item structure. Finally, three BMI-groups were compared using the person parameter estimates from the RSM for evidence of construct validity.

Rating Scale Model Calibration

The first assumption for Rasch analysis is that a scale is unidimensional. Even though the BSIQ was divided into nine subscales based on factor analysis in which each subscale represented one independent unidimensional scale, the data were analyzed to confirm the unidimensionality of each subscale using principal component analysis in the SPSS program. From principal component analysis, only one component (i.e., factor) was extracted in each subscale. The percents of variance explained by the extracted component were from 58.07 to 82.47 for the nine subscales.

Each subscale with the original categorization and items was calibrated using the RSM. The results from the initial calibration were examined to determine the optimal categorization and to detect misfitting items.

Categorization

The RSM was found to be a good fit in the initial calibration for the categorizations of all subscales in regard to frequencies, hierarchical order in average measures and step calibrations, and Outfit mean squares. No disordered categories were found in terms of average measures and step calibrations in the initial calibration. However, step calibrations for the FE, SD, HD, and II subscales didn't advance enough as suggested in the guidelines (Linacre, 2002). In Table 5, the distance between the categories 3 and 4 was narrower than 1.0 logit for the SD, HD, and II subscales (see step advance values). For the FE subscale, the advances between the categories 3 and 4 and between the categories 4 and 5 were less than 1.0 logit. Therefore, collapsing process was applied to the categorization of these four subscales.

Combining the categories 3 and 4 into one category (recoded as 12334) was applied to the SD, HD, and II subscales because only one violation of step calibration advance was found on the third step calibration for each subscale. For the FE subscale, three collapsing combinations combining the (a) categories 3 and 4 (recoded as 12334), (b) categories 4 and 5 (recoded as 12344), and (c) categories 3, 4, and 5 (recoded as 12333) were applied.

Information about corresponding average measures, Outfit mean squares, and step calibrations for the collapsed four-point categorization are presented in Table 6. For the SD, HD, and II subscales, combining the categories 3 and 4 was acceptable based on the guidelines and improved category function. After the collapsing, average measures and step calibrations were ordered in respective subscales as observed in the initial calibration. For the SD subscale, step calibrations were -2.35, -.74, and 3.09 for thresholds between the first and second, second and third, third and fourth categories, respectively. All advances between step calibrations were

larger than 1.0 logit. For the HD subscale, step calibrations were -2.77, -.67, and 3.45. For the II subscale, step calibrations were -2.29, -.87, and 3.16.

For the FE subscale, combining the categories 3 and 4 (i.e., 12334) was better than other collapsing combinations because all measures were ordered and step calibrations (-1.61, -.48, and 2.10) advanced enough (1.13 and 2.58). In addition, the combination 12334 provided better statistics such as person separation (2.34), person reliability (.85), item separation (18.81), and item reliability (1.00). In contrast, the combination 12344 still resulted in a small advance between the second (.43) and third (.56) step calibrations. Even though no violation of category function was found in the combination 12333, collapsing five categories into three resulted in the loss of information about respondents (person separation = 1.85; person reliability = .77) and slightly deteriorated the quality of the subscale (item separation = 17.47) compared to combination 12334. Therefore, a collapsed categorization combining the categories 3 and 4 was chosen for the FE, SD, HD, and II subscales while the original five-point categorization was retained for the OAE, AG, HFE, HFI, and NA subscales. The graphs representing the changes after the collapsing categories for the SD, HD, and II subscales are presented in Figures 1, 2, and 3, respectively. Because the misfitting item treatment was required for the FE subscale, the category probability curves for the subscale are presented in the next section.

Misfitting Item Deletion

Item fit statistics were examined to detect misfitting items after investigating the category function of each subscale and determining the optimal categorization for the subscales with problematic categorization. Any items which had Infit and Outfit statistics smaller than .6 or larger than 1.4 were considered misfit.

In the FE subscale, two misfitting items were found. Fit statistics for item 22 (I have large buttocks) were 1.62 for Infit mean square and 1.66 for Outfit mean square. Item 35 (My stomach is flabby) was also misfitting and fit statistics for this item were 1.44 and 1.51 for Infit and Outfit mean squares, respectively. Because these fit statistics for item 22 and 35 were obtained after categories 3 and 4 were combined and these two items were also misfitting with the original five-point categorization (Infit = 1.72 and Outfit = 1.80 for item 22; Infit = 1.42 and Outfit = 1.55 for item 35), an investigation as to what caused this was conducted. It might be that the pattern of category function of misfitting items, which worked differently from the categorization of the other fitting items, affected the category function of the FE subscale. If this is true, it might not be necessary to collapse the original five-point categorization into four when the two misfitting items were deleted from the FE subscale. To investigate this concern, the function of the original five-point categorization for the FE subscale was again checked after items 22 and 35 were deleted without collapsing any categories. As a result, no disordered measures were found but the step calibrations for the original categorization were -2.18, -.26, .57, and 1.88 indicating that the advance between the second and third step calibration was smaller than 1.0 logit. This result supported collapsing the third and fourth categories for the FE subscale. Therefore, items 22 and 35 were deleted from the FE subscale and the collapsed categorization (12334) was kept without further concerns. The data were recalibrated for the FE subscale with items 22 and 35 deleted from the subscale and with the collapsed four-point categorization to obtain the category function statistics. All measures were ordered and each step calibration advanced larger than 1.0 logit. The final category function statistics for the FE subscale are presented in Table 7. The category probability curves for the FE subscale representing the change of categorization after collapsing categories and item deletion are presented in Figure 4.

In the NA subscale, one item was misfitting. The fit statistics for item 11 (being around good-looking people makes me feel sad about my body) were 1.45 and 1.55 for Infit and Outfit mean squares, respectively. The original categorization was retained for the NA subscale in the investigation of the categorization function. Therefore, item 11 was deleted from the NA subscale without the additional checking which was conducted in the FE subscale.

Finally, no misfitting items were found in other subscales. Therefore, all items in the OAE, AG, HFE, HFI, SD, HD, and II subscales were retained.

Parameter Estimation

The data were recalibrated for each subscale after optimizing categorization and deleting misfitting items. Item and person parameter estimates were obtained from the last calibration.

Item Parameter Estimation

Item parameter estimates (i.e., measures) are presented in Table 8. Figures 5 through 13 show the person-item maps for respective subscales. In each Figure, participants and body self-image items were arranged along the vertical axis (i.e., common metric in logits) in order of the level of parameter estimates. For the OAE subscale, item difficulties ranged from -.52 to .48. As presented in Figure 5, item 26 (my body looks good) was the most difficult to endorse (i.e., choose) while item 17 (I look good in clothes) was the easiest. Differently from ability and achievement tests, the item difficulties of the BSIQ items indicate the endorsability of items by participants based on related body self-image satisfaction or dissatisfaction. For the FE subscale, item difficulties ranged from -2.38 to 2.23. Item 18 (my body is fat overall) was least endorsable and item 14 (parts of my body are fat) was most endorsable as presented in Figure 6. For the AG subscale, item difficulties ranged from -.37 to .62. As presented in Figure 7, item 20 (I spend time making my appearance more attractive) was least frequently endorsed and item 6 (I pay

careful attention to my face and hair, so that I will look good) was most frequently endorsed. For the HFE subscale, item difficulties ranged from -1.13 to .58. As presented in Figure 8, item 34 (I have an athletic build) was least endorsable while item 13 (my body is healthy) was most endorsable. For the HFI subscale, item difficulties ranged from -1.42 to .91. Item 36 (my body image is influenced by the state of my health) was least frequently endorsed while item 30 (the way I feel about my body improves when I exercise regularly) was most frequently endorsed as presented in Figure 9. For the SD subscale, item difficulties ranged from -.18 to .25. As presented in Figure 10, item 4 (my thoughts about my body depend on the clothes I'm wearing) was least frequently endorsed and item 8 (I compare my body to people I'm close to) was most frequently endorsed. For the HD subscale, item difficulties ranged from -.64 to .72. As presented in Figure 11, item 38 (if I were a different height, I'd like my body better) was least endorsable and item 2 (I've often wanted to be taller) was most endorsable. For the NA subscale, item difficulties ranged from -.52 to .69. Item 19 (my naked body makes me angry) was least endorsable and item 5 (my naked body makes me feel sad) was most endorsable (Figure 12). For the II subscale, item difficulties ranged from -.58 to .59. As presented in Figure 13, item 16 (muscle definition is important to me) was least endorsable while item 9 (having a well-proportioned body is important to me) was most endorsable among the II items.

Person Parameter Estimation

Person parameter estimates, also called person abilities, were obtained from the final calibration for each subscale. In this study, person abilities indicate the perceived level of body self-image satisfaction or dissatisfaction. For subscales inquiring body self-image satisfaction (e.g., OAE, HFE, and HFI), higher measures imply higher satisfaction and vice versa. As mentioned in earlier section, person parameter estimates were calibrated on the metric where

item parameter estimates were located. Therefore, it was possible to compare person and item measures on the same yardstick. In addition, the parameter estimates, person and item measures, were interval-level data transformed from ordinal-level data by the Rasch calibration. Therefore, measures were used for the analysis of group mean difference in which the linearity of data was assumed.

Validation

From the cross-validation process, the optimal categorization was examined with the same criteria used in the collapsing process and the stability of item structure of the BSIQ was cross-validated by investigating the pattern of item difficulties in each subscale.

If the hierarchical item order and item fit statistics differ largely in spite of the invariance feature of IRT, the items would represent different constructs to each sample of participants and would limit quantitative comparisons (Andrich, 1988). In addition, consistent categorization across the samples would confirm the participants' stable perception of the categorization of the BSIQ.

Cross-Validation with Reduced Sample Size

Cross-validation was conducted to examine the patterns of categorization and retained items of the BSIQ using a smaller sample (the validation sample, $n = 510$) that was randomly selected from the total sample. The RSM model was applied to the validation sample with the revised categorization and items. This procedure was done to confirm the optimal categorization of each subscale, and to investigate the stability of item parameter estimates and the sensitivity of the model to the smaller sample size.

Categorization

The patterns of the categorizations for each subscale in the validation sample were similar to the categorizations for each subscale in the total sample. For the OAE, AG, HFE, HFI, and NA subscales, the original five-point categorization was kept for the total sample. The results from the calibration using the cross-validation sample were also consistent with the categorizations in the total sample. Average measures and step calibrations were hierarchically ordered. Outfit mean squares for categories for each subscale were within the criterion of 2.0. Step calibrations were -4.08, -1.65, 1.15, and 4.58 for the OAE, -3.74, -1.04, .92, and 3.86 for the AG, -3.12, -1.35, .73, and 3.75 for the HFE, -2.12, -.98, .76, and 2.34 for the HFI, and -3.02, -.53, .93, and 2.62 for the NA subscale. All steps for each subscale advanced more than 1.0 and less than 5.0 logits.

For the FE subscale, two items (I22 and I35) were misfitting in the validation sample as in the total sample calibration. Therefore, the two missing items were deleted for the recalibration. For the FE subscale, the collapsed four-point categorization (i.e., combination 12334) was chosen for the total sample. The collapsed four-point categorization also worked well for the validation sample. Average measures and step calibrations were hierarchically ordered and Outfit mean squares for each category (1.02, .83, 1.07, and 1.06) were within the criteria. The step calibrations were –2.58, -.43, and 3.00 so, each step advance between step calibrations met the criteria. Because the collapsed categorization drawn from the total sample was applied to the validation sample for the FE subscale, the category function of the original five-point categorization was also checked again using the validation sample. The results were identical with the total sample calibration. Items 22 and 35 were misfitting and step calibrations were -1.43, -.11, .39, and 1.16 indicating that step advances between the second and third and

between the third and fourth step calibrations were smaller than 1.0 logit. Therefore, the collapsed four-point categorization was confirmed for the FE subscale in the validation sample.

For the SD subscale, the collapsed four-point categorization (combination 12334) worked well for the validation sample. All average measures and step calibrations were ordered and all step advances were larger than 1.0 and smaller than 5.0 logits (-2.35, -.78, and 3.13). In calibration with the original five-point categorization, however, step advance between the second and third step calibrations was smaller than 1.0 logit. Therefore, the collapsed combination 12334 was confirmed for the SD subscale in the validation sample.

For the HD subscale, the collapsed four-point categorization (combination 12334) was working well in the validation sample. All average measures and step calibrations were ordered and all step advances were larger than 1.0 and smaller than 5.0 logits (-2.87, -.77, and 3.64). In calibration with the original five-point categorization, however, the original five-point categorization also worked well in terms of hierarchically ordered measures and step calibrations, Outfit statistic, and step advances. Subsequently, separation statistics for the original and collapsed categorizations were compared to determine which categorization discriminated items and persons better for the HD subscale in the validation sample. Person separation statistics were 1.67 for the original categorization and 1.51 for the collapsed. In the comparison of item separation, the original categorization (5.89) provided a better statistic than the collapsed (5.14). Therefore, the collapsed four-point categorization chosen from the total sample calibration for the HD subscale was not confirmed in the validation sample.

For the II subscale, the collapsed four-point categorization (combination 12334) was chosen in the total sample calibration and the collapsed categorization was confirmed in the validation calibration. All average measures and step calibrations were ordered and Outfit mean

squares for categories were within the criteria. Step advances were -2.48, -.80, and 3.28 so, all steps advanced more than 1.0 and less than 5.0 logits. In checking again the optimal categorization for the II subscale, step calibrations for the original categorization were -2.29, -.26, .37, and 2.18 indicating the narrow distance (<1.0 logit) between the second and third step calibrations.

To summarize, the collapsed and retained categorizations for subscales were confirmed in the cross-validation except for the HD subscale in which the original categorization provided better item and person separation statistics.

Item Fit and Order

From the 39 items of the BSIQ, 36 items were retained in the total sample calibration so these 36 retained items were administered to the cross-validation calibration. For the validation sample, the Infit and Outfit statistics for all items for all subscales were acceptable based on the criteria ($.60 \leq$ fit ≤ 1.40) and the hierarchical order of item measures in each subscale was identical to the total sample calibration.

To compare the item measures for the validation sample to the item measures for the total sample, refer to the item measures for the total sample in Table 8. The item measures for the validation sample are reported here. For the OAE subscale, item measures were -.15, -.53, .57, and .11 for the items 10, 17, 26, and 32, respectively. For the FE subscale, item measures were 1.14, -2.35, 2.25, .79, and –1.79 for the items 7, 14, 18, 29, and 39, respectively. For the AG subscale, item measures were -.42, -.18, and .60 for the items 6, 12, and 20, respectively. For the HFE subscale, item measures were .39, -1.26, .52, -.34, .52, and .17 for the items 3, 13, 21, 28, 34, and 37, respectively. For the HFI subscale, item measures were .57, -1.42, and .85 for the items 23, 30, and 36, respectively. For the SD subscale, item measures were .23, -.16, and -.08

for the items 4, 8, and 15, respectively. For the HD subscale, item measures from the calibration with the original categorization (recoded as 12345) were used for the comparison because the original categorization worked better for the validation sample. Item measures with the original categorization were -.58, -.03, and .61 for the items 2, 25, and 38, respectively. For the NA subscale, item measures were -.51, .65, -.04, and -.10 for the items 5, 19, 27, and 33, respectively.

The hierarchical order of items was consistent across the samples. The 36 item measures as a function of invariance estimates in two samples were plotted in Figure 14. The slope of the straight line was set at 1.0 indicating the invariance of item estimates from each sample. Therefore, if an item functioned differently from a sample to another, the item would be plotted away from the straight line. All items were plotted close to the straight line indicating the invariance of item estimates across samples.

Construct Validity

To provide evidence of construct validity for the Rasch calibrated measures and the revised categorization of the BSIQ, the mean person body self-image measures in logits for three groups formed based on BMI scores were compared for each subscale using a one-way ANOVA with alpha level of .05 (see Table 9. In addition, the group means were contrasted using the *t*-test for two independent groups with alpha level of .02 to examine which groups significantly differenced.

Significant differences were found in the OAE, FE, and NA subscales (Table 9). The results from the contrasts are presented in Table 10. For the OAE subscale, the normal group (M = 1.03 and SD = 2.62) scored significantly higher than the overweight group (M = -.44 and SD = 2.80) for overall appearance evaluation. The underweight group (M = 1.76 and SD = 2.83) also

scored significantly higher than the overweight group. No significant difference was found between the underweight and normal groups.

For the FE subscale, all contrasts were significant. Because higher measures represent higher dissatisfaction for fatness evaluation, the participants in the underweight group (M = -4.22 and SD = 2.24) scored significantly lower than the normal group (M = -2.02 and SD = 3.28), the normal group scored significantly lower than the underweight & obesity group (M = 1.04 and SD = 3.04), and the underweight group mean was lower than the overweight group.

For the NA subscale, significant differences were found between the normal and overweight groups, and between the underweight and overweight groups. Because higher measures represent higher dissatisfaction with body self-image, the normal group (M = -2.87 and SD = 2.69) scored significantly lower than the overweight group (M = -1.54 and SD = 3.06) and the mean (-3.59 with SD = 2.15) of the underweight group was significantly lower than the mean of the overweight group.

Even though significant differences were not found in the other subscales, consistent tendencies were observed that the underweight group scored higher across the satisfaction subscales and lower in the dissatisfaction subscale. The results from the analysis of group mean differences provided evidence of construct validity. The participants were well-discriminated in terms of person measures in each subscale according to the level of respondents' body self-image satisfaction.

Discussion

The collapsed four-point categorization for the HD subscale from the total sample calibration was not confirmed in the validation sample calibration. Determination of the optimal categorization was based on the guidelines suggested by Linacre (2002). However, it is

somewhat questionable to collapse categories when the guidelines are applied strictly even though collapsing categories affects the measurement quality. For example, the original categorization for the HD subscale was collapsed into a four-point categorization in the total sample calibration due to the step advance (.96) from the second to third step calibrations, which was smaller than 1.0 logit. However, the collapsing of categories decreased the person and item separation statistics from 1.56 (person reliability = .71) and 8.63 (item reliability = .99) to 1.50 (person reliability = .69) and 7.80 (item reliability = .98), respectively. Similar results were found in the SD and II subscales while collapsing categories for the FE subscale increased person separation and decreased item separation statistic. Even though it is recommended to collapse adjacent categories to improve category function in terms of measures and statistics as suggested in the guidelines (Linacre, 2002), it seems that satisfying the guidelines does not always improve the psychometric quality of a scale as observed in the present study. Ewing, Salzberger, and Sinkovics (2005) also suggested that inclusion of other criteria such as maximizing the item and person separations might alter the decisions made to collapse adjacent categories. In the present study, all measures and step calibrations were hierarchically ordered and each category had its own boundary. Therefore, the original categorization may be kept for the all subscales of the BSIQ instead of employing two different sets of categorization; the original categorization for certain subscales and the collapsed categorization for the other subscales.

The Rasch analysis also provided information about misfitting items related to other latent variables rather than corresponding body image traits. Three misfitting items were detected by the Rasch analysis and these items were deleted from subsequent analyses. The three items were items 22 and 35 for the FE subscale and item 11 for the NA subscale. The items were also

identified as misfit in the validation sample calibration. Therefore, it is possible that the items are related to other dimensions not shared by the remaining items. However, misfitting items should be deleted with a caution especially when the fit statistics for the misfitting items are within a mean square of 2.0. According to Linacre (2004a) items with fit statistics ranged from 1.5 to 2.0 may be unproductive for construction of measurement but do not degrade the quality of measurement. Therefore, deleting items depends on the researcher's purpose of research. In the present study, for the FE subscale, Infit and Outfit mean squares were 1.72 and 1.80 for item 22, and 1.42 and 1.55 for item 35. For item 11, Infit and Outfit mean squares were 1.45 and 1.55, respectively. The fit statistics for these items were very close to the cutoff values except item 22 and one or either statistics was within the range of 1.5 to 2.0 indicating unproductive but no degrading measurement. Even though the three misfitting items were deleted from the BSIQ according to the guidelines to demonstrate the application of the Rasch analysis in the present study, another criteria representing the quality of measurement (e.g., separation statistics) might be applied and investigated to confirm the decision for deleting misfitting items. In the present study, deleting two misfitting items from the FE subscale increased both item and person separation statistics from 19.23 (item reliability = 1.00) and 2.25 (person reliability = .84) to 26.82 (item reliability = 1.00) and 2.35 (person reliability = .85) while deleting item 11 from the NA subscale decreased both item and person separation statistics from 9.89 (item reliability = .99) and 1.93 (person reliability = .79) to 7.02 (item reliability = .98) and 1.88 (person reliability = .78). Therefore, deleting the two misfitting items from the FE subscale seems reasonable to improve the quality of the BSIQ while deleting item 11 from the NA subscale is questionable. If it is the case of developing a questionnaire, it is recommended to revise the items in terms of wording of the statements.

The stability of item parameter estimation across the different sample sizes was examined. Zhu (2002) reported the correlation of item measures generated from two Rasch rating scale analyses and the rank correlation of the item severity orders to investigate the invariance of the Rasch estimation. In the present study, however, the correlation of item measures obtained from the total and validation samples was not estimated due to the relatively small number of items. Instead, hierarchical order of item measures was compared. Item orders from the two samples were identical. Small amount of changes in fit statistics and item measures were observed. However, differences between the two estimations were relatively small or minimal.

Construct validity was conducted to investigate whether the Rasch calibrated measures of the BSIQ imply the trait of body self-image satisfaction. Significant differences were found in the OAE, FE, and NA subscales from the ANOVA with alpha level of .05. Consequently, the group means for the subscales with significant differences were contrasted using the *t*-test for two independent groups with alpha level of .02 to examine which groups significantly differenced. Significant difference between the underweight and normal groups was found in the FE subscale ($p = .00$). The differences between the underweight and overweight groups were significant in the OAE ($p = .00$), FE ($p = .00$), and NA ($p = .00$) subscales. The differences between the normal and overweight groups were also significant in the OAE ($p = .00$), FE ($p = .00$), and NA ($p = .00$) subscales. Although it was not a major part of the study, person measures estimated from the total sample ($N = 1021$) were also examined based on the same grouping method using BMI. Significant differences were found in the OAE, FE, HFE, HD, and NA subscales. In other subscales that didn't have significant differences among groups, participants in higher BMI group tended to endorse lower categories in the body self-image

satisfaction subscales and higher categories in the dissatisfaction subscales. This additional result was consistent with the result of the group mean comparisons for the validation sample.

The measurement quality of the BSIQ should be discussed in terms of the variety of item difficulties and the number of items. The item difficulties were somewhat limited to a small range. For example, item difficulties for the SD subscale ranged from -.18 to .25 in logits. Since the range of difficulty is normally from -3.0 to +3.0 (Baker, 1985), the item difficulties for the SD subscales are very limited. As presented in Figure 10 and seen in Table 8, items cover only a small part of person abilities that ranged from -4 to +4. Consequently, person separation (1.09) and reliability (.54) for this subscale were relatively low because the scale items identified individual differences not as effective as other subscale items such as the FE (person separation = 2.40 and reliability = .85). The lack of items and the limited item difficulty range also resulted in many maximal and minimal extreme scores (by respondents who assigned the highest categories for all items or lowest categories for all items). Even though measures are assigned to those extreme cases with the estimation process, the accuracy of estimation and the quality of measurement decrease as the number of extreme cases increases. Therefore, it is recommended to add more items with various item difficulties to each subscale of the BSIQ to identify respondents' ability and individual differences effectively.

For the comparison between the observed scores (i.e., raw scores) and the Rasch calibrated person measures, there was a strong relationship. For example, the correlation between the raw scores and the person measures in logits for the OAE subscale was .99. For this reason, it may be questioned why the Rasch calibrated measures should be used instead of the total scores (i.e., subscale scores in this study) which is calculated from ordinal scales. The Rasch calibrated measures do not have any of the fundamental measurement concerns which are the critical issues

in the application of CTT to ordinal data. Because the Rasch calibrated measures are statistically proven to have the characteristics of interval data, it is desirable to use the Rasch measures over the ordinal data to calculate total or subscale scores. As presented in Figure 15, the relationship between the raw scores and the person measures in logits is curvilinear. For the raw subscale scores (i.e., vertical axis in Figure 15), one integer increment from 5 to 6 is the same as the increment of 1 from 11 to 12. However, the distances between 5 and 6 and 11 and 12 are not likely to be the same for the person measures in logits (horizontal axis in Figure 15). Therefore, calculating total scores from ordinal scales may mislead researchers in interpreting the results, so converting raw scores from an ordinal scale to linear measures using the Rasch analysis is necessary to compare differences and changes on a linear continuum.

Table 5

Rating Scale Model Category Function Statistics for the Original Categorization

Subscale	Response category	Observed		Average measure	Expected measure	Outfit MnSq	Step calibration	Step advance
		Count	%					
OAE	1	148	4%	-3.16	-3.31	1.28	None	
	2	667	17%	-1.80	-1.71	.91	-3.99	None
	3	1358	35%	.01	.02	.86	-1.59	2.40
	4	1325	34%	2.26	2.17	.94	1.10	2.69
	5	357	9%	3.90	4.07	1.18	4.47	3.37
FE	1	1939	31%	-2.31	-2.25	1.07	None	
	2	1512	24%	-.95	-1.05	.84	-1.37	None
	3	964	16%	-.07	-.13	1.02	-.12	1.25
	4	894	14%	.59	.69	1.15	.36	.48
	5	891	14%	1.61	1.61	1.11	1.14	.78
	Missing	2	0%	-1.29				
AG	1	92	3%	-2.71	-2.74	1.02	None	
	2	464	16%	-1.16	-1.12	.92	-3.53	None
	3	802	28%	.34	.35	.94	-.92	2.61
	4	1080	38%	1.95	1.89	.99	.81	1.73
	5	427	15%	3.40	3.48	1.08	3.64	2.83
HFE	1	505	8%	-2.75	-2.69	1.08	None	
	2	1198	20%	-1.48	-1.43	.87	-2.90	None
	3	2037	34%	-.18	-.20	.80	-1.36	1.54
	4	1735	29%	1.45	1.35	1.04	.69	2.05
	5	506	8%	3.11	3.38	1.29	3.56	2.87
	Missing	1	0%	-2.30				
HFI	1	134	5%	-1.52	-1.85	1.43	None	
	2	360	13%	-.86	-.75	.94	-2.26	None
	3	724	26%	.21	.30	.90	-.93	1.33
	4	902	32%	1.61	1.52	.89	.68	1.61
	5	673	24%	2.93	2.95	1.04	2.51	1.83

Table 5 (*Continued*).

Subscale	Response category	Observed		Average measure	Expected measure	Outfit MnSq	Step calibration	Step advance
		Count	%					
SD	1	297	10%	-1.44	-1.62	1.22	None	
	2	768	26%	-.83	-.72	.87	-2.11	None
	3	744	25%	.10	.09	.85	-.27	1.84
	4	750	26%	.89	.85	.90	.46	.73
	5	381	13%	1.64	1.64	1.03	1.92	1.46
HD	1	381	18%	-2.45	-2.58	1.26	None	
	2	658	31%	-1.46	-1.34	.83	-2.52	None
	3	459	22%	-.14	-.14	.76	-.37	2.15
	4	403	19%	1.18	751.08	.89	.59	.96
	5	229	11%	2.33	2.37	1.22	2.30	1.71
NA	1	1377	34%	-3.20	-3.13	.99	None	
	2	1341	33%	-1.68	-1.74	.88	-2.43	None
	3	729	18%	-.36	-.43	.84	-.46	1.97
	4	398	10%	.83	.76	1.00	.77	1.23
	5	195	5%	1.79	2.11	1.55	2.12	1.35
II	1	176	4%	-.99	-1.33	1.49	None	
	2	672	14%	-.40	-.34	1.01	-2.13	None
	3	1028	22%	.40	.45	.84	-.36	1.77
	4	1632	35%	1.28	1.29	.89	.39	.75
	5	1221	26%	2.40	2.36	1.01	2.10	1.71

Note. OAE = Overall Appearance Evaluation; FE = Fatness Evaluation; AG = Attention to Grooming; HFE = Health Fitness Evaluation; HFI = Health Fitness Influence; SD = Social Dependence; HD = Height Dissatisfaction; NA = Negative Affect; II = Investment in Ideals. MsSq indicates mean square error. If a step advance is larger than 5.0 or smaller than 1.0, the categorization is considered problematic.

Table 6

Rating Scale Model Category Function Statistics for the Collapsed Categorization

Subscale	Response category	Observed		Average measure	Expected measure	Outfit MnSq	Step calibration	Step Advance
		Count	%					
FE	1	1939	31%	-2.75	-2.72	1.12	None	
	2	1512	24%	-.99	-1.05	.78	-1.61	None
	3 (3+4)	1858	30%	.49	.51	1.05	-.48	1.13
	4	891	14%	2.27	2.28	1.05	2.10	2.58
	Missing	2	0%	-1.44				
SD	1	297	10%	-1.81	-1.92	1.15	None	
	2	768	26%	-.94	-.83	.87	-2.35	None
	3 (3+4)	1494	51%	.83	.79	.89	-.74	1.61
	4	381	13%	2.55	2.58	1.02	3.09	3.83
HD	1	381	18%	-2.81	-2.90	1.26	None	
	2	658	31%	-1.58	-1.45	.78	-2.77	None
	3 (3+4)	862	40%	.88	.81	.90	-.67	2.10
	4	229	11%	3.26	3.30	1.08	3.45	4.12
II	1	176	4%	-1.22	-1.62	1.52	None	
	2	672	14%	-.40	-.28	.92	-2.29	None
	3 (3+4)	2660	56%	1.35	1.38	.86	-.87	1.42
	4	1221	26%	3.39	3.34	.95	3.16	4.03

Note. FE = Fatness Evaluation; SD = Social Dependence; HD = Height Dissatisfaction; II = Investment in Ideals. MsSq indicates mean square error. Response 3 (3+4) stands for the combined third and fourth categories of the original categorization. If a step advance is larger than 5.0 or smaller than 1.0, the categorization is considered problematic.

Table 7

Rating Scale Model Category Function Statistics for the Fatness Evaluation (FE) Subscale with the Collapsed Categorization after the Deletion of Items 22 and 35

Subscale	Response category	Observed		Average measure	Expected measure	Outfit MnSq	Step calibration	Step Advance
		Count	%					
FE	1	1335	32%	-4.17	-4.15	.99	None	
	2	1052	25%	-1.46	-1.47	.79	-2.49	None
	3 (3+4)	1220	29%	.96	.89	1.17	-.47	2.02
	4	598	14%	3.60	3.68	1.08	2.96	3.43

Note. MsSq indicates mean square error. Response 3 (3+4) stands for the combined third and fourth categories of the original categorization. If a step advance is larger than 5.0 or smaller than 1.0, the categorization is considered problematic.

Table 8

Rating Scale Model Item Fit Statistics for the Retained Items with the Optimal Categorization in Each Subscale

Subscale	Item Number	Item	Raw score	Count	Measure	Error	Infit	Outfit
OAE	I10	Naked body OK	3220	964	-.18	.06	1.35	1.35
	I17	Good in clothes	3330	964	-.52	.06	.94	.93
	I26	Body looks good	3004	964	.48	.05	.71	.71
	I32	Sexually appealing	3087	963	.22	.06	.96	.95
FE	I07	Looks fat in clothes	1624	841	1.10	.07	.85	.87
	I14	Partly fat	2470	841	-2.38	.06	1.02	1.11
	I18	Fat overall	1387	841	2.23	.07	.99	1.02
	I29	Overweight	1683	841	.84	.07	.88	.81
	I39	Wish thinner	2327	841	-1.79	.06	1.15	1.10
AG	I06	Attention to face & hair	3435	955	-.37	.05	.77	.76
	I12	Usually well dressed	3390	955	-.25	.05	1.18	1.20
	I20	Time to be attractive	3056	955	.62	.05	1.01	1.00
HFE	I03	Overall fit high	2928	997	.36	.05	.92	.95
	I13	Body is healthy	3557	997	-1.13	.05	1.09	1.12
	I21	Muscle tone good	2905	996	.41	.05	.76	.77
	I28	Body is strong	3231	997	-.34	.05	1.05	1.05
	I34	Athletic build	2831	997	.58	.05	1.37	1.34
	I37	Body in shape	3030	997	.13	.05	.71	.72
HFI	I23	Body function	3124	931	.51	.04	.93	.94
	I30	Exercise regularly	3959	931	-1.42	.05	1.28	1.20
	I36	State of my health	2916	931	.91	.04	.86	.85
SD	I04	Clothes dependence	2532	980	.25	.05	1.00	.99
	I08	Comparing to people	2671	980	-.18	.06	1.07	1.04
	I15	Social awareness	2636	980	-.07	.06	.93	.90

Table 8 (*Continued*).

Subscale	Item number	Item	Raw score	Count	Measure	Error	Infit	Outfit
HD	I02	Want to be taller	1872	710	-.64	.07	1.16	1.15
	I25	Different height	1751	710	-.08	.07	.72	.69
	I38	Different HT better	1576	710	.72	.07	1.12	1.13
NA	I05	Naked body sad	1668	677	-.52	.06	.98	.97
	I19	Naked body angry	1342	677	.69	.06	1.22	1.08
	I27	Depressed about body	1514	677	.02	.06	.87	.85
	I33	Feel bad about body	1575	677	-.20	.06	.97	.98
II	I01	Control fat level	2863	946	.07	.06	1.16	1.15
	I09	Well proportioned body	3024	946	-.58	.07	.74	.70
	I16	Muscle definition	2720	946	.59	.06	1.09	1.12
	I24	Legs shaped	2817	946	.24	.06	1.02	1.00
	I31	Size matters	2960	945	-.32	.06	.98	.95

Note. OAE = Overall Appearance Evaluation; FE = Fatness Evaluation; AG = Attention to Grooming; HFE = Health Fitness Evaluation; HFI = Health Fitness Influence; SD = Social Dependence; HD = Height Dissatisfaction; NA = Negative Affect; II = Investment in Ideals.

Table 9

One-Way Analysis of Variance for the Person Body Self-Image Measures Among the Three Body Mass Index (BMI) Groups

Subscale	Source	*df*	*F*	*p*
Overall appearance evaluation	Between groups	2	14.573*	.000
	Within groups	500		
	Total	502		
Fatness evaluation	Between groups	2	50.729*	.000
	Within groups	500		
	Total	502		
Attention to grooming	Between groups	2	2.573	.077
	Within groups	500		
	Total	502		
Health fitness evaluation	Between groups	2	2.053	.129
	Within groups	500		
	Total	502		
Health fitness influence	Between groups	2	.480	.619
	Within groups	500		
	Total	502		
Social dependence	Between groups	2	.313	.732
	Within groups	500		
	Total	502		
Height dissatisfaction	Between groups	2	2.572	.077
	Within groups	500		
	Total	502		
Negative affect	Between groups	2	11.665*	.000
	Within groups	500		
	Total	502		

Table 9 (*Continued*).

Subscale	Source	*df*	*F*	*p*
Investment in ideals	Between groups	2	.815	.443
	Within groups	500		
	Total	502		

Note. * $p < .05$.

Table 10

Contrast (t-test) Among the Three Body Mass Index (BMI) Groups

Subscale	Contrast	Std. Error	*df*	*t*	*p*
Overall appearance evaluation	1	.4907	41.165	1.483	.146
	2	.3096	153.867	4.740*	.000
	3	.5468	60.975	4.015*	.000
Fatness evaluation	1	.4139	50.882	-5.323*	.000
	2	.3464	172.599	-8.830*	.000
	3	.4819	82.293	-10.919*	.000
Attention to grooming	1	.4937	40.169	1.601	.117
	2	.2489	179.481	1.094	.275
	3	.5226	49.775	2.033	.047
Health fitness evaluation	1	.4779	39.231	-.114	.909
	2	.2558	153.028	1.979	.050
	3	.5181	53.114	.872	.387
Health fitness influence	1	.3628	39.791	-.669	.508
	2	.1840	171.103	-.475	.636
	3	.3861	50.302	-.855	.397
Social dependence	1	.4130	40.481	.045	.964
	2	.2256	168.538	-.820	.413
	3	.4443	53.171	-.375	.709
Height dissatisfaction	1	.4681	44.815	-.288	.775
	2	.3449	160.746	-2.165	.032
	3	.5356	71.174	-1.646	.104
Negative affect	1	.3843	46.624	-1.871	.068
	2	.3340	147.641	-3.979*	.000
	3	.4685	87.577	-4.371*	.000

Table 10 (*Continued*).

Subscale	Contrast	Std. Error	*df*	*t*	*p*
Investment in ideals	1	.4419	39.872	.325	.747
	2	.2328	165.454	1.189	.236
	3	.4740	51.908	.887	.379

Note. Equal variances were not assumed. Contrast 1 = underweight group vs. overweight group; contrast 2 = underweight group vs. normal group; contrast 3 = normal group vs. overweight group. * $p < .02$.

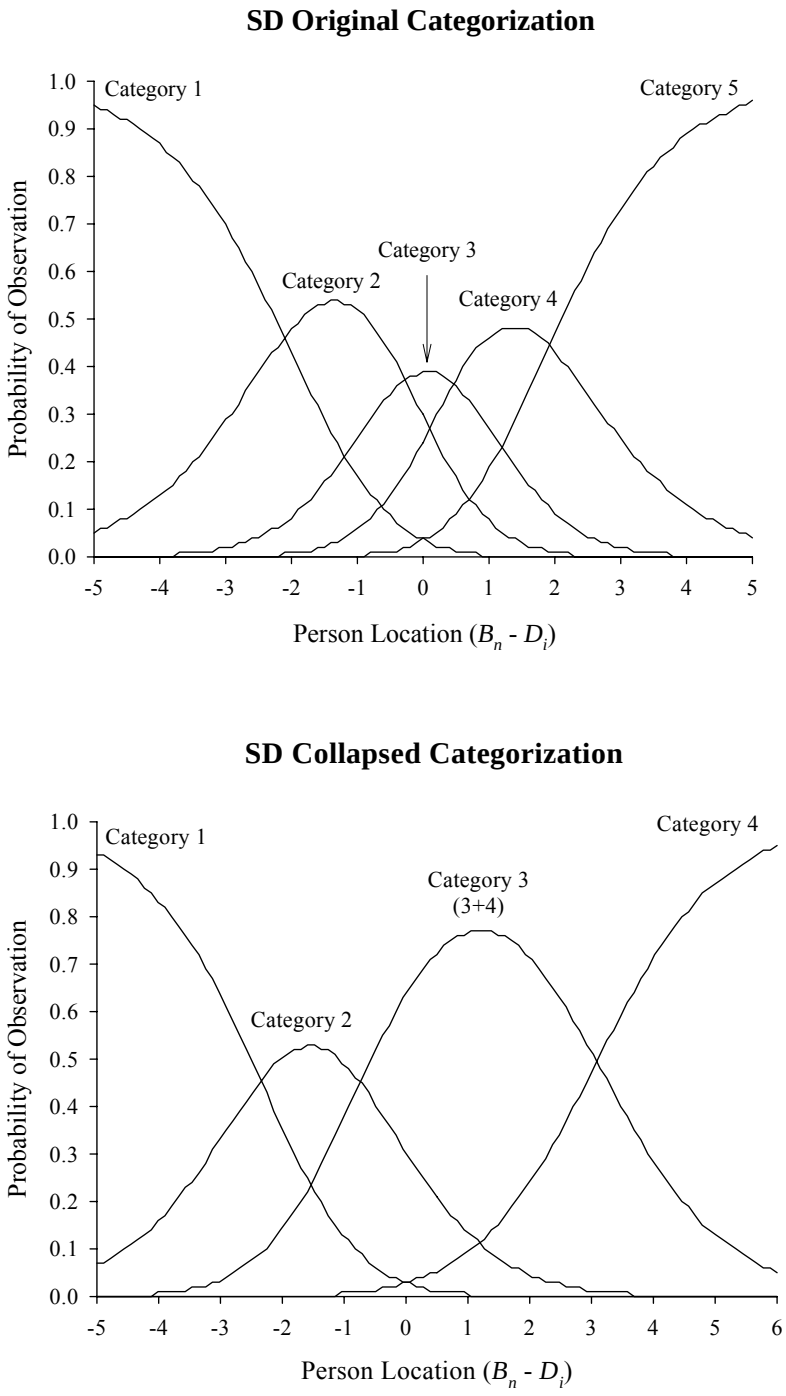


Figure 1. Rating scale model category probability curves for the original and collapsed categorizations for the social dependence (SD) subscale.

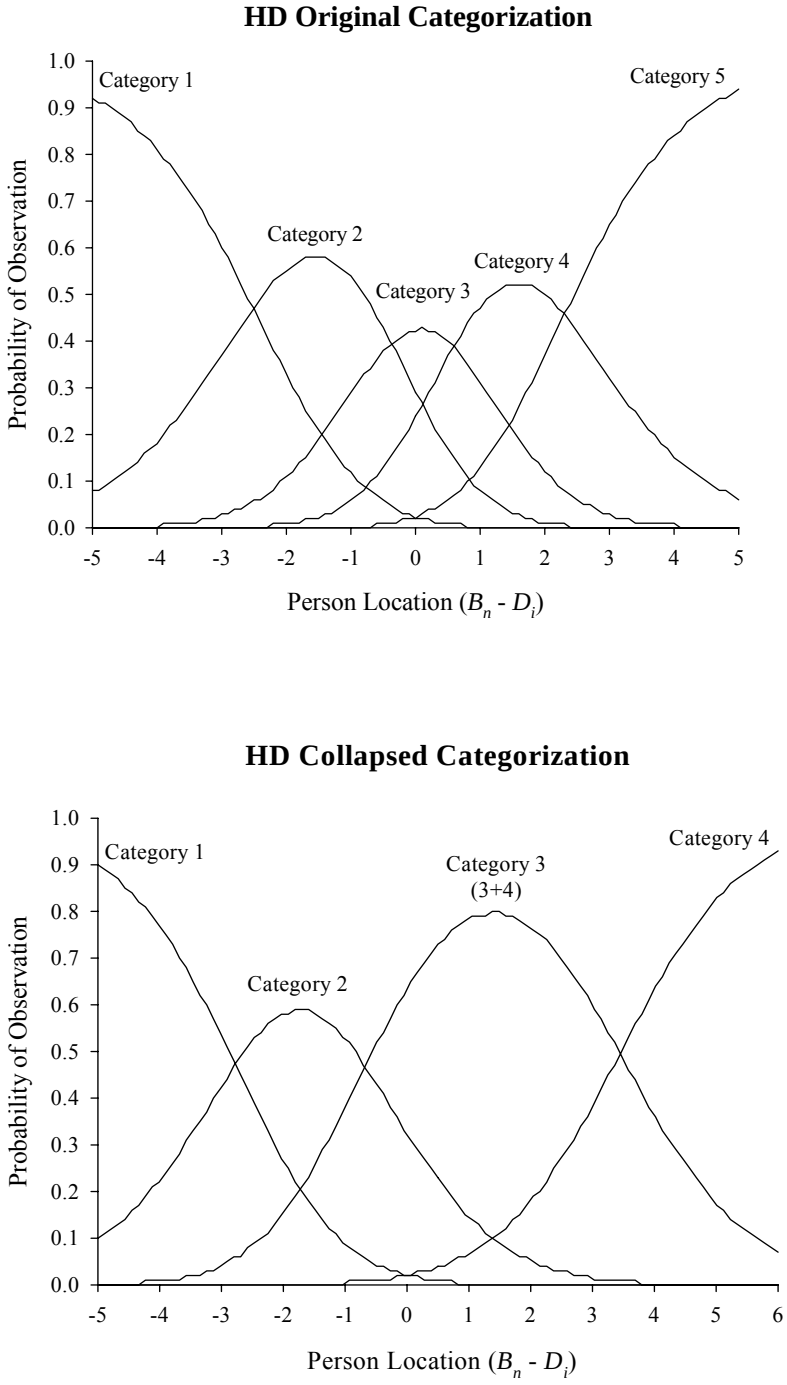
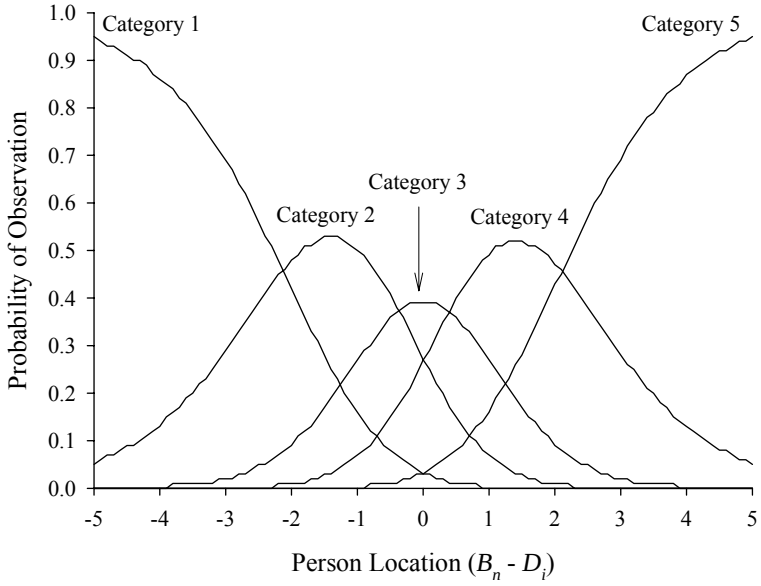


Figure 2. Rating scale model category probability curves for the original and collapsed categorizations for the height dissatisfaction (HD) subscale.

II Original Categorization



II Collapsed Categorization

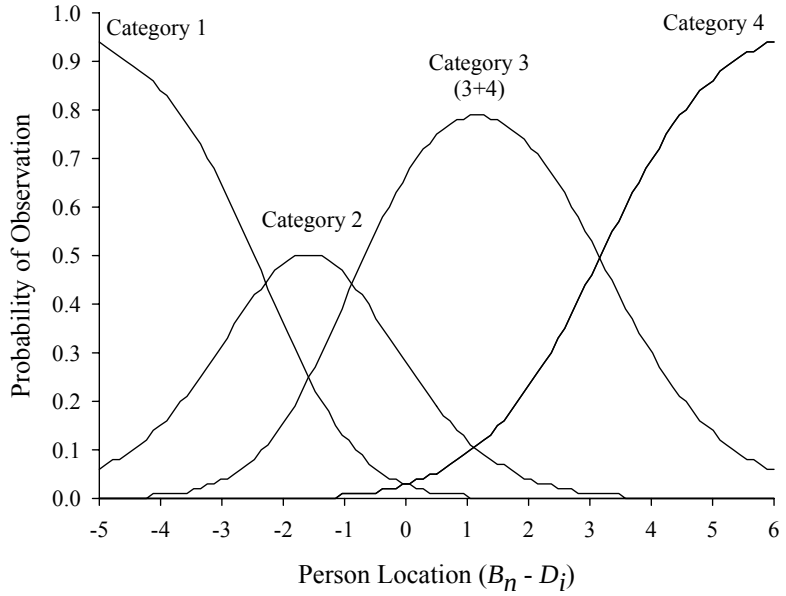


Figure 3. Rating scale model category probability curves for the original and collapsed categorizations for the investment in ideals (II) subscale.

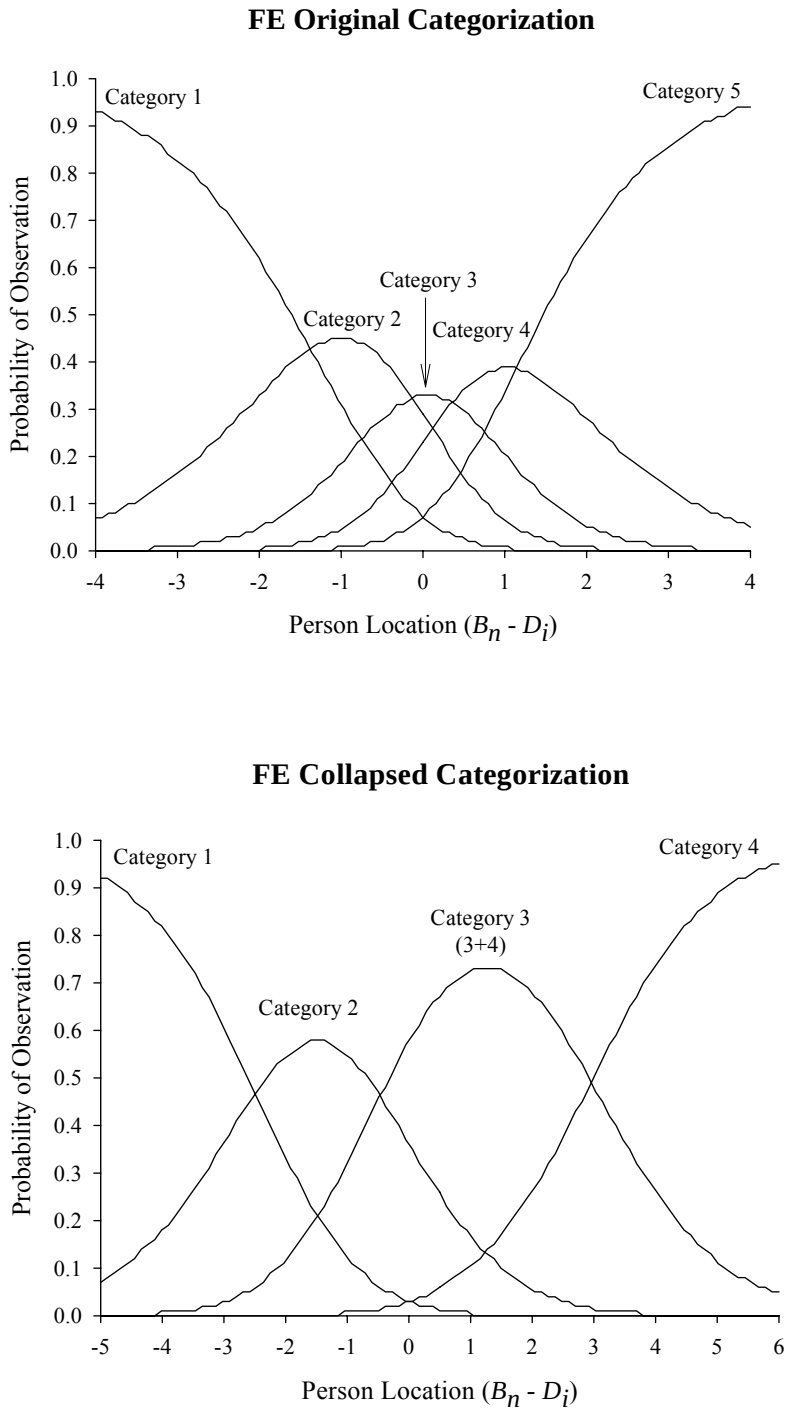


Figure 4. Rating scale model category probability curves for the original and collapsed categorizations for the fatness evaluation (FE) subscale after the deletion of the items 22 and 35.

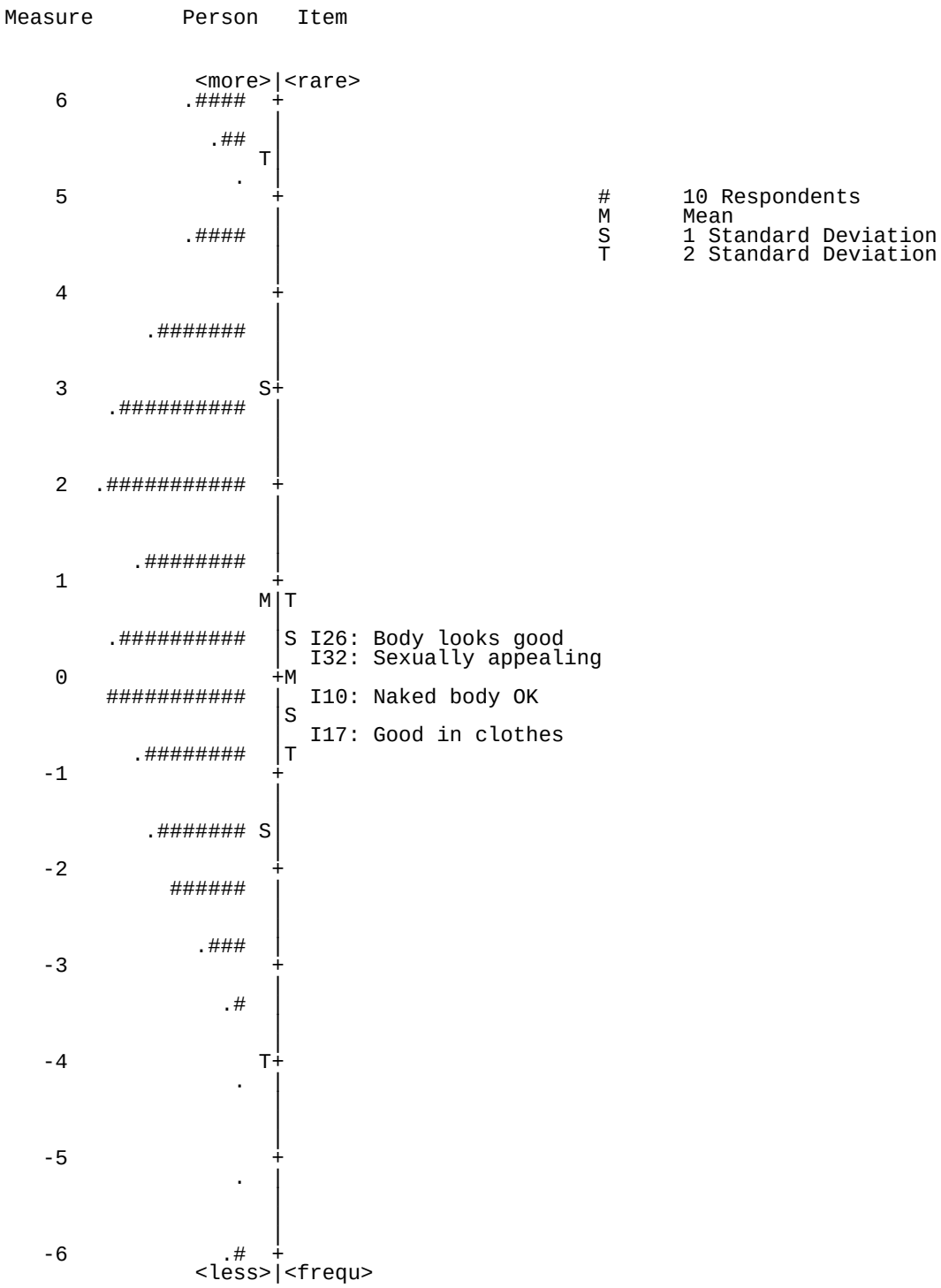


Figure 5. Map for the person and item parameter estimates for the overall appearance evaluation (OAE) subscale.

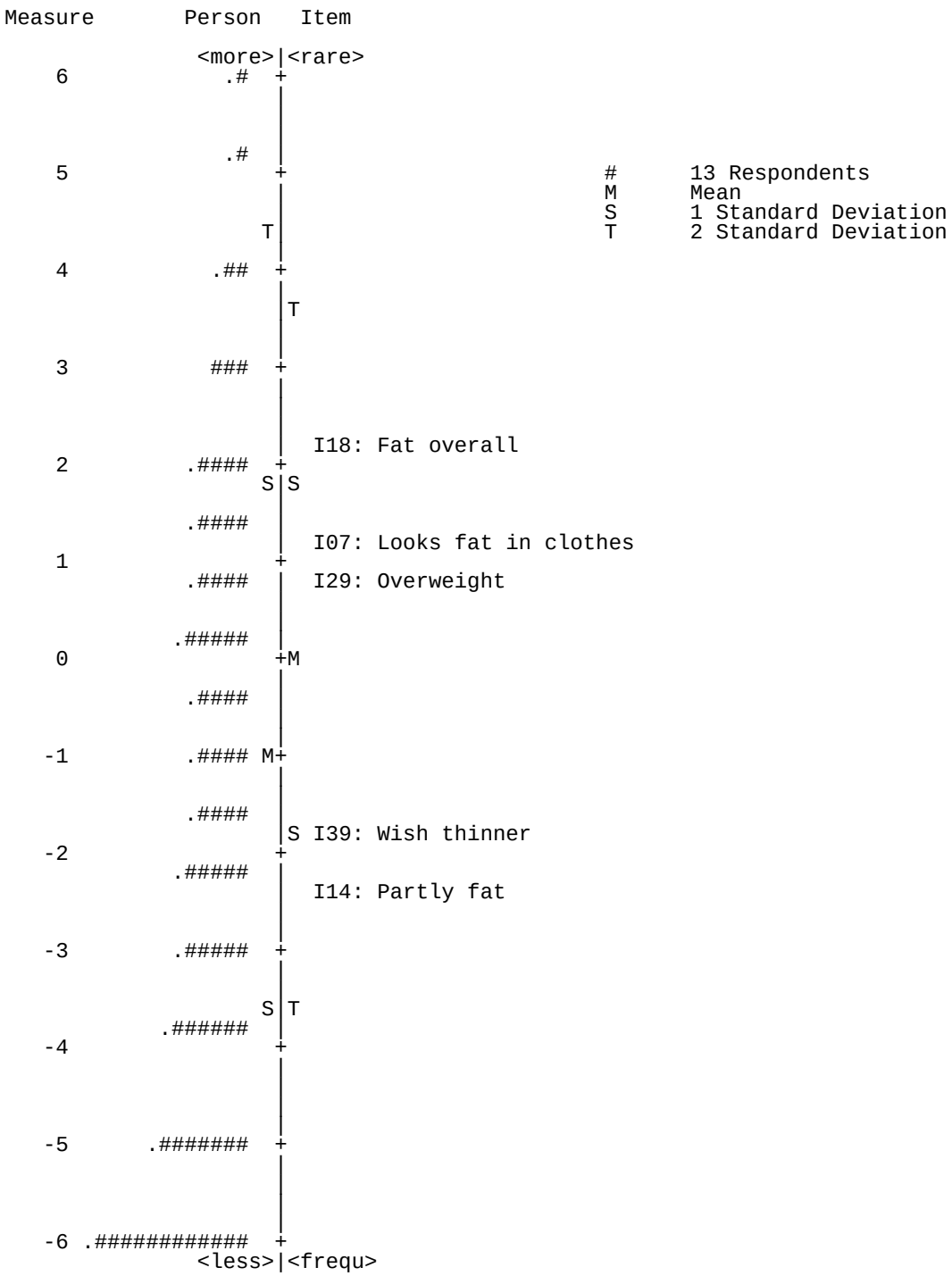


Figure 6. Map for the person and item parameter estimates for the fatness evaluation (FE) subscale.

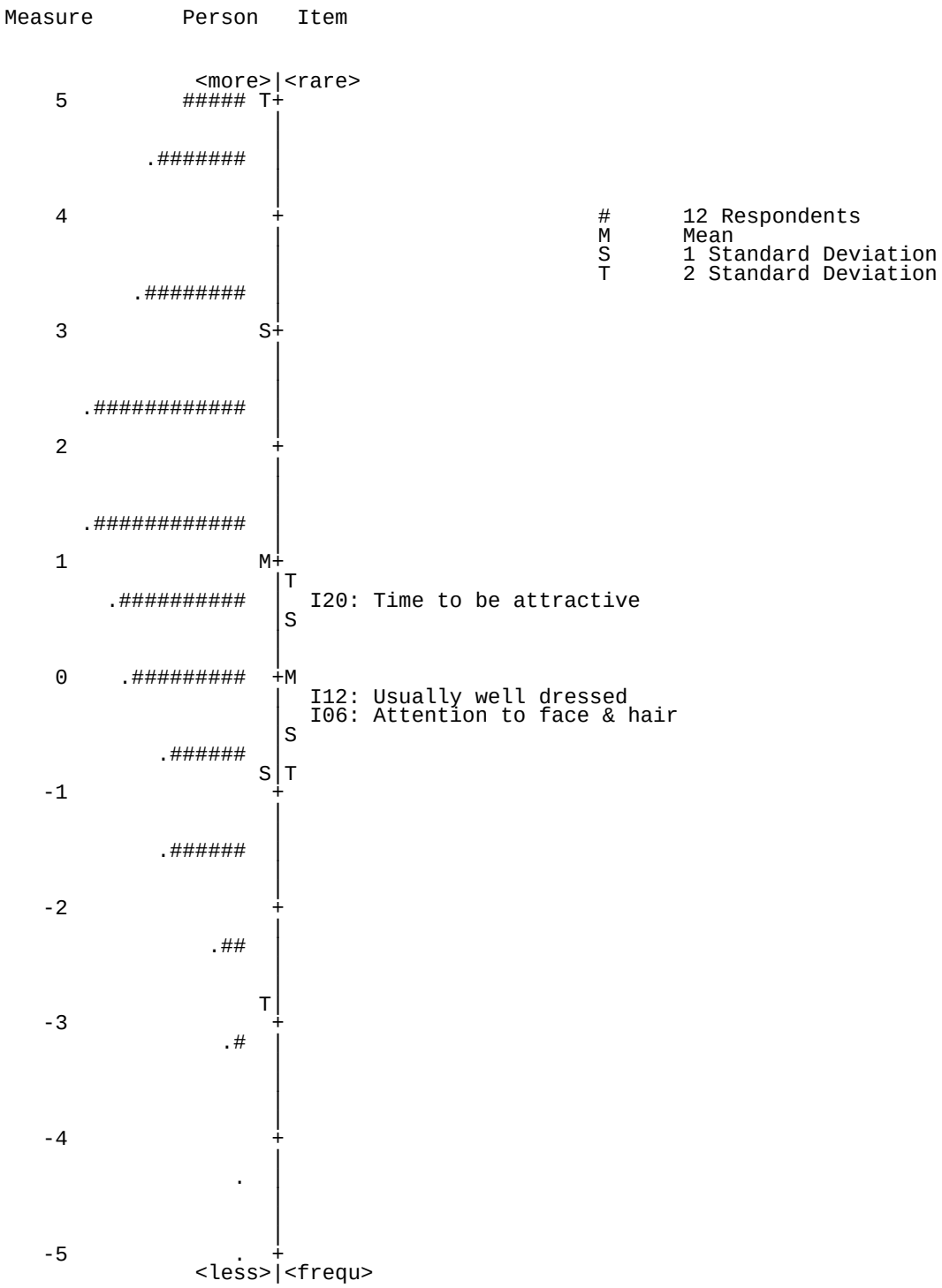


Figure 7. Map for the person and item parameter estimates for the attention to grooming (AG) subscale.

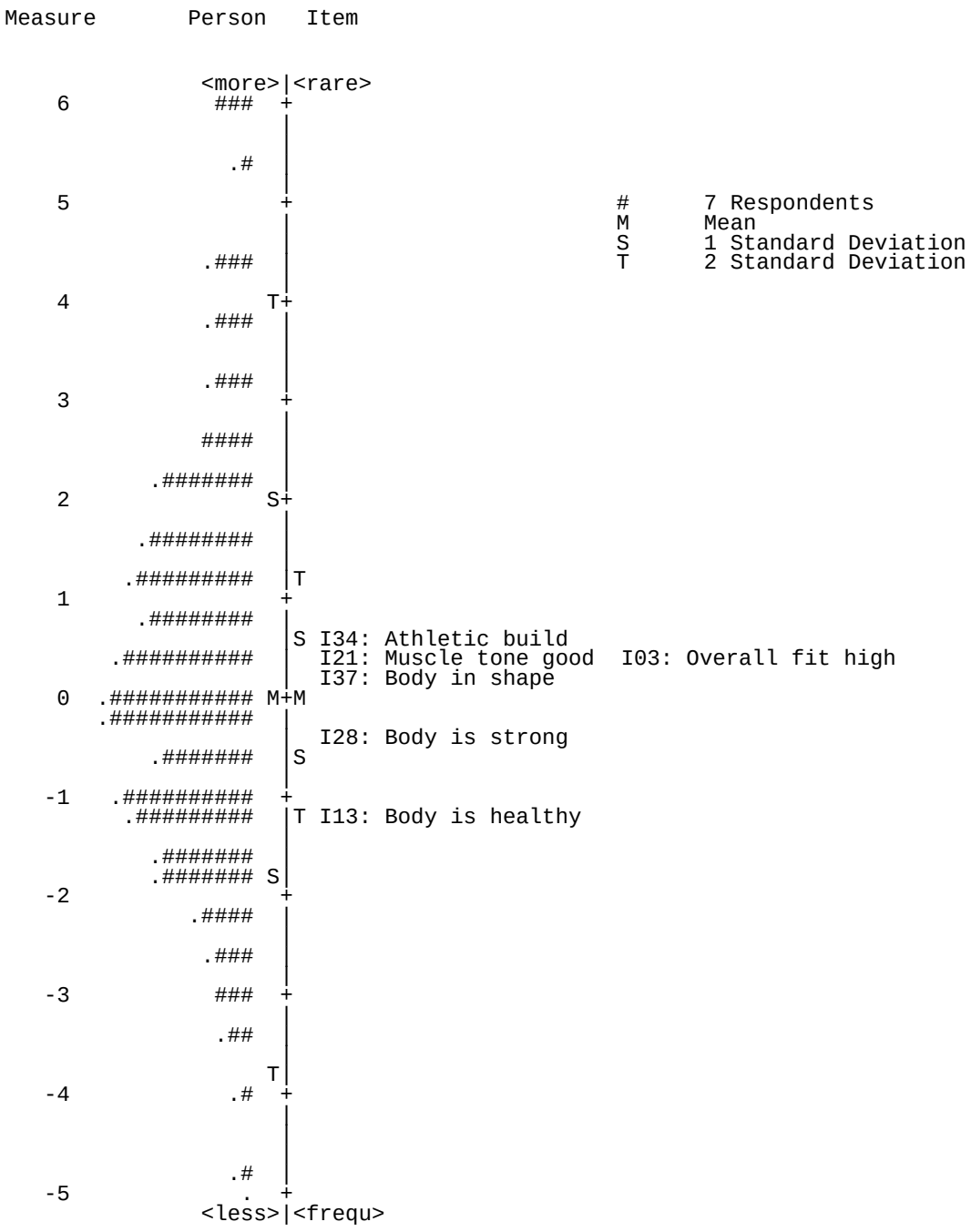


Figure 8. Map for the person and item parameter estimates for the health fitness evaluation (HFE) subscale.

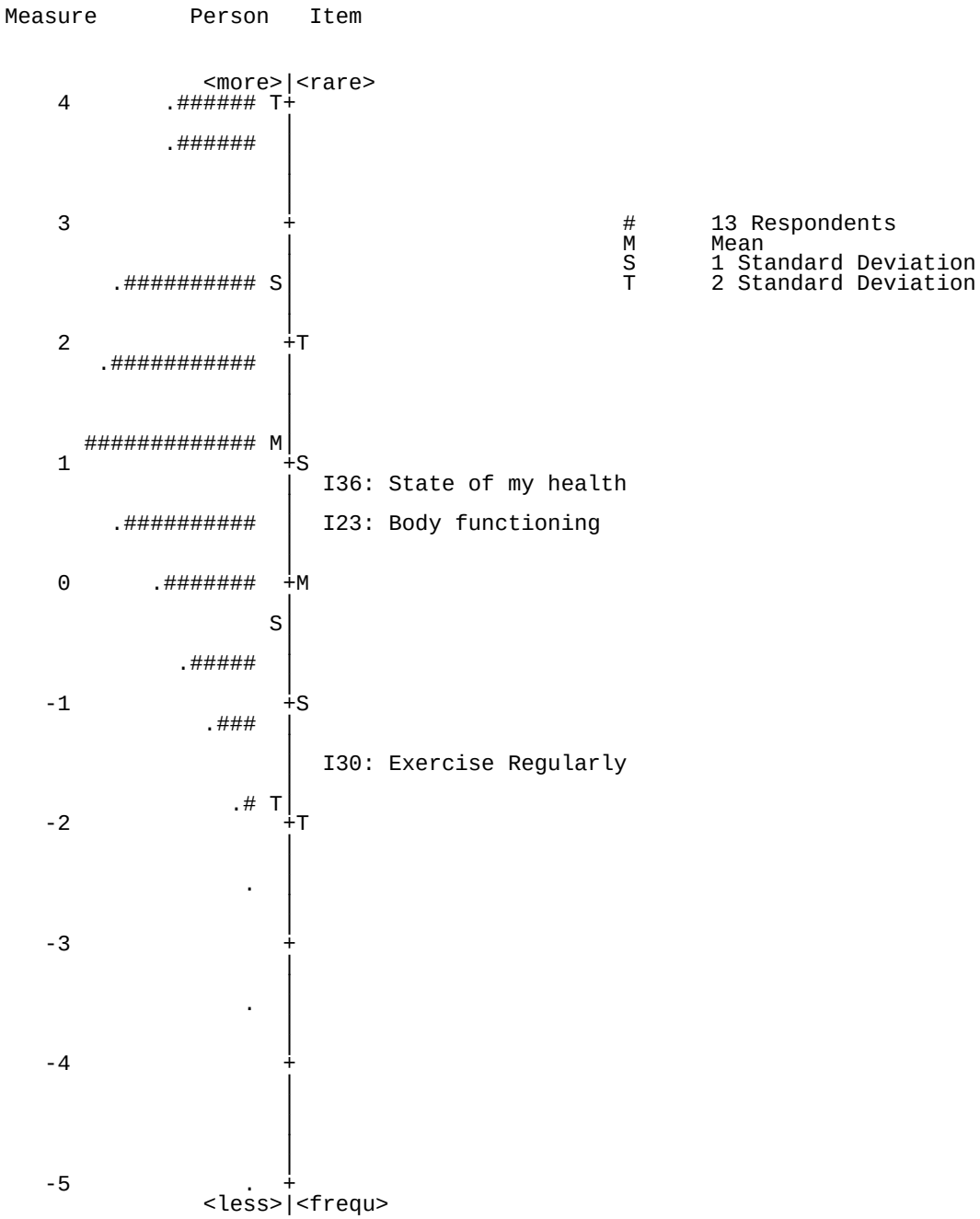


Figure 9. Map for the person and item parameter estimates for the health fitness influence (HFI) subscale.

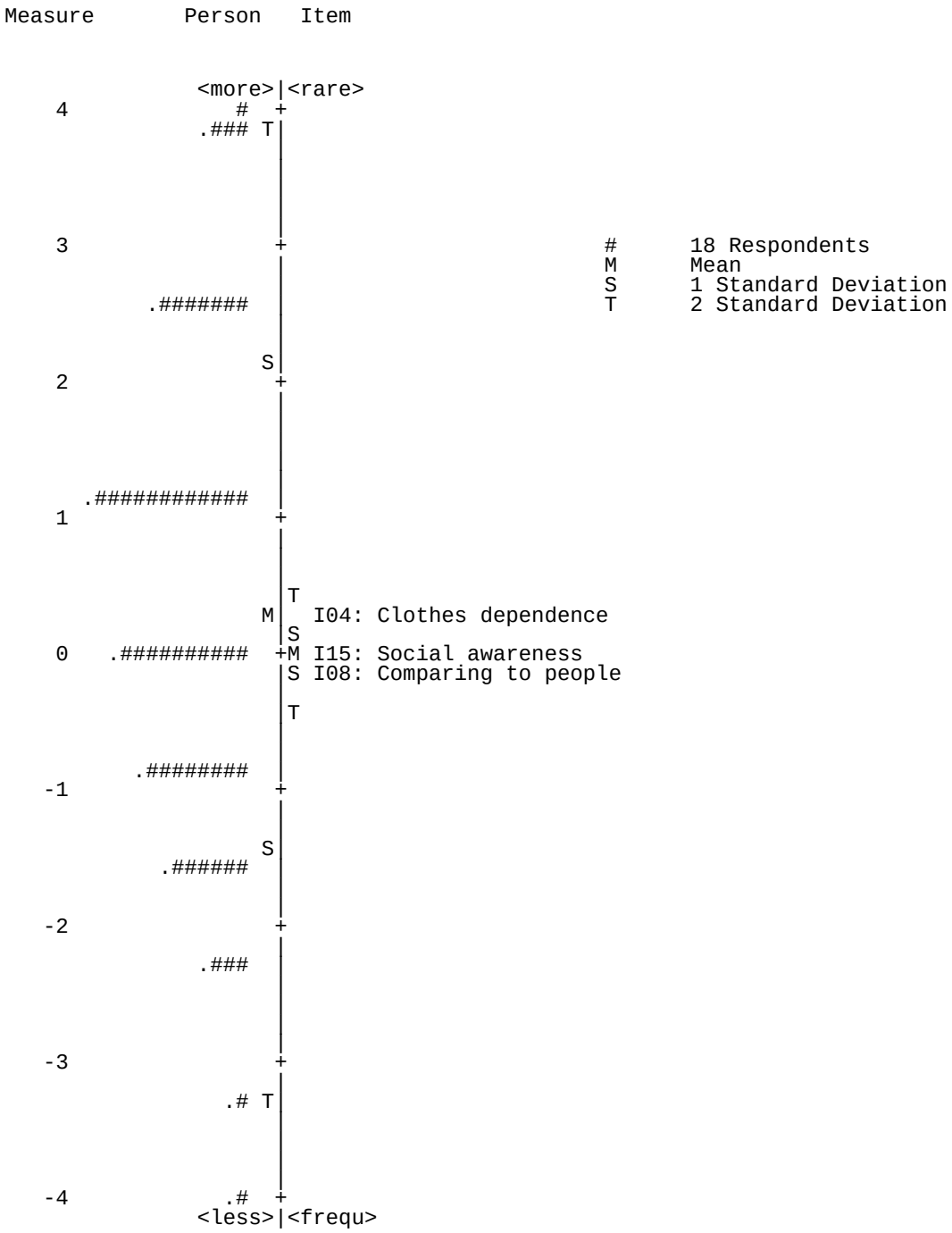


Figure 10. Map for the person and item parameter estimates for the social dependence (SD) subscale.

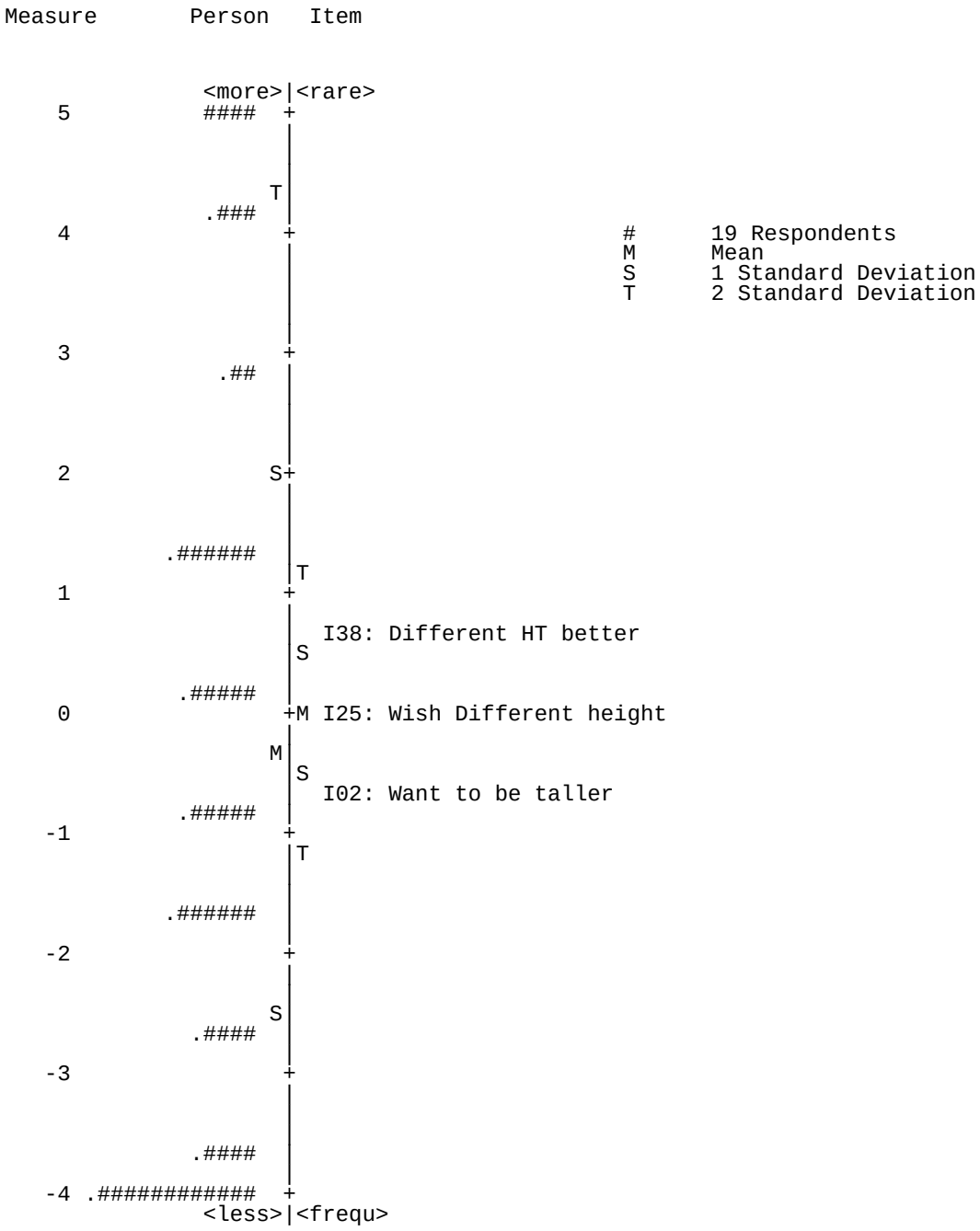


Figure 11. Map for the person and item parameter estimates for the height dissatisfaction (HD) subscale.

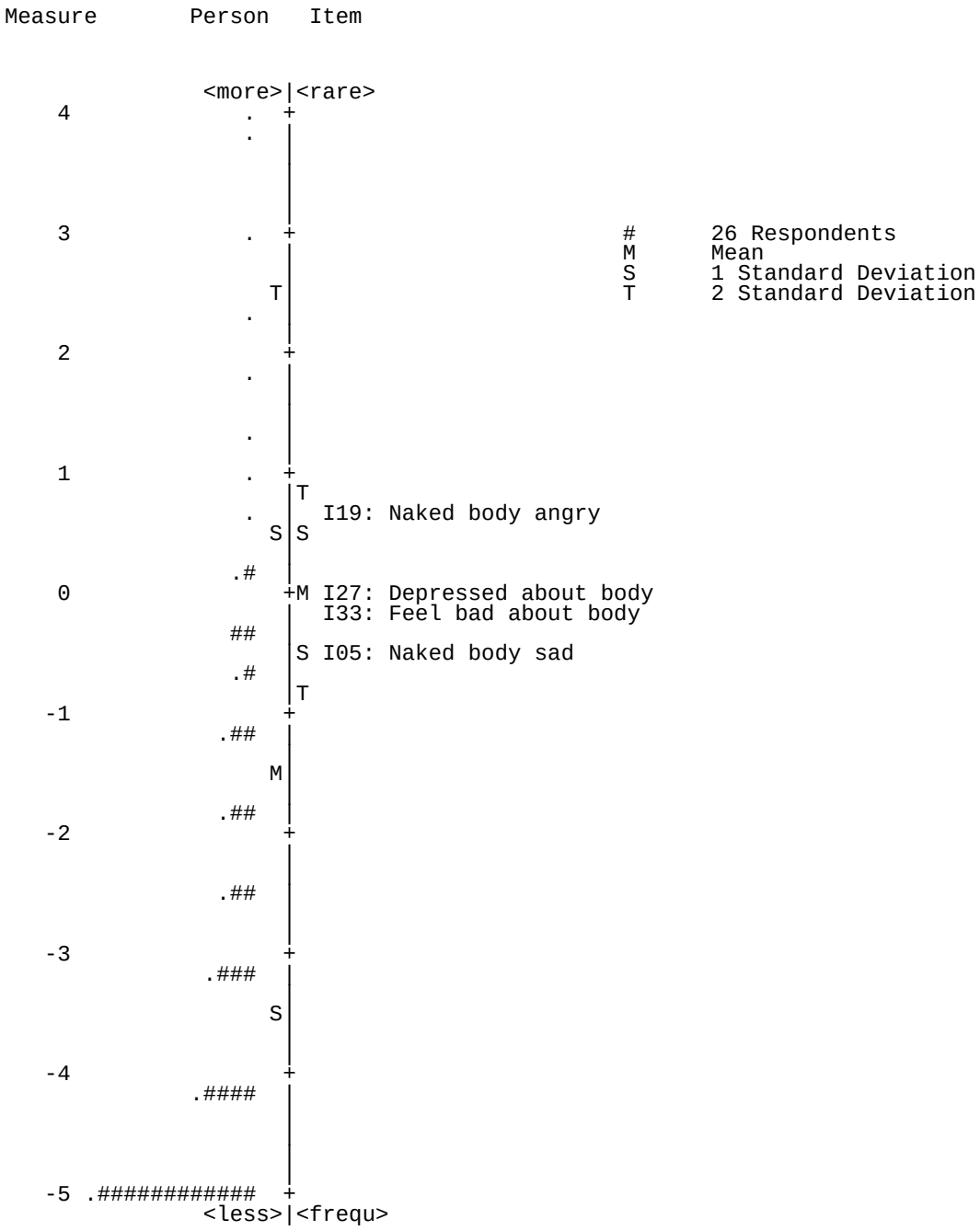


Figure 12. Map for the person and item parameter estimates for the negative affect (NA) subscale.

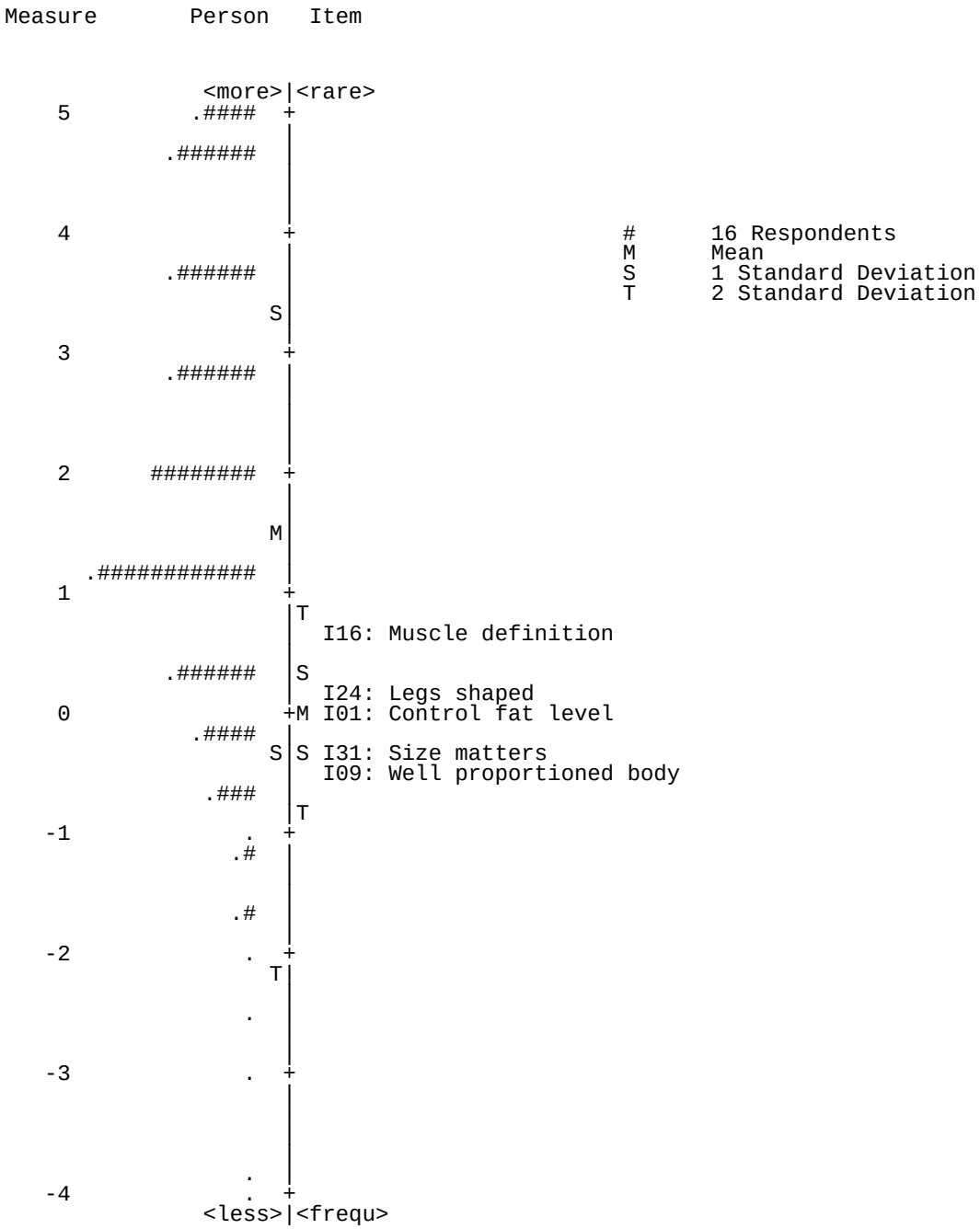


Figure 13. Map for the person and item parameter estimates for the Investment in Ideals (II) subscale.

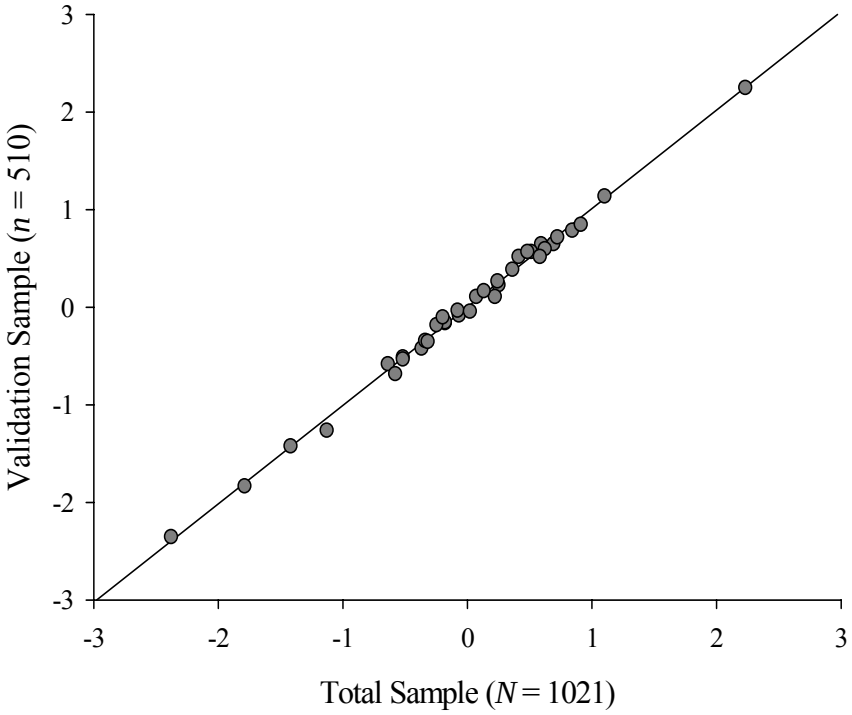


Figure 14. Differential item functioning of the Body Self-Image Questionnaire (BSIQ) in the total sample and the validation sample. The slope of the regression line is 1.0 and the unit of the measures is logits.

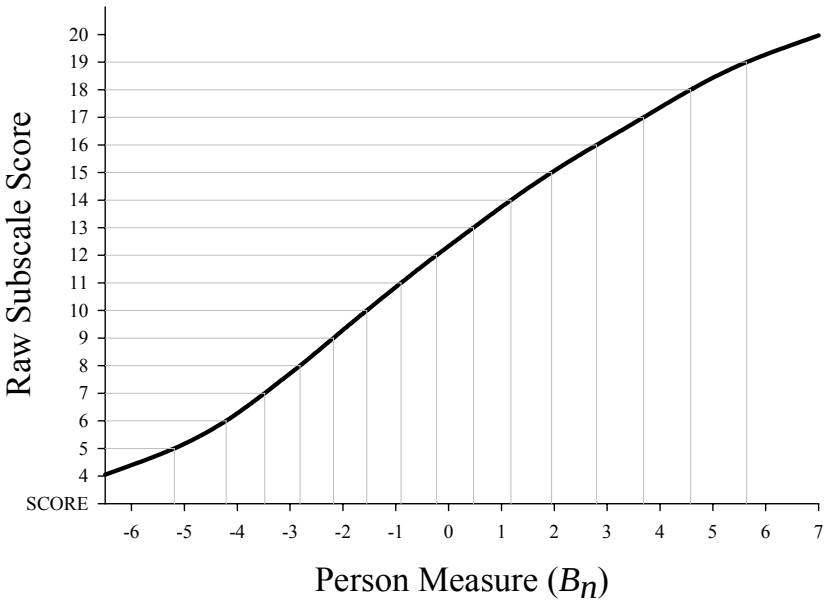


Figure 15. Curvilinear relationship between the raw scores and the Rasch calibrated person measures for the Overall Appearance Evaluation (OAE) subscale.

CHAPTER 5

SUMMARY AND CONCLUSSIONS

The present study was designed to evaluate the application of the Rasch analysis to converting ordinal data into interval data, to optimizing the number of categories, and to constructing items for each subscales of the BSIQ. The data from 1021 undergraduate students were used in this study. The analysis was conducted on each of the nine subscales of the BSIQ.

Summary

The Rasch analysis using the RSM provided information concerning determining the optimal categorization for the subscales of the BSIQ. From the series of RSM calibrations, the four-point categorization was found appropriate for the FE, SD, HD, and II subscales and the original five-point categorization was retained for the other subscales. The collapsed categorization and the original categorization determined in the total sample calibration were confirmed in the validation sample calibration except for the categorization for the HD subscale. The different result for the HD subscale have resulted from the different category endorsement patterns across the samples. Even though the validation sample was drawn randomly from the total sample, the endorsement pattern may not be controlled.

The Rasch analysis detected misfitting items in the total sample and validation sample calibrations. The misfitting items may be related to other latent variables rather than the body self-image trait. Even though the misfitting items were deleted from subsequent analyses to demonstrate the application of the Rasch analysis strictly according to the guidelines, the results

can be used for reconstructing items for a scale in a different way. Because only numerical and empirical aspects of item fit were examined in this study, linguistic aspects of items such as the choice of relevant words and clarity of statements should be examined and revised before deleting misfitting items especially when developing a scale or a questionnaire.

Item and person parameter estimates for each subscale were obtained from the final calibration for the total sample after optimizing categorization and deleting misfitting items. The estimates were linear measures which were converted from observed scores obtained from an ordinal scale. Therefore, comparing item difficulties and person abilities (i.e., body self-image satisfaction and dissatisfaction) on the same yardstick without linearity concerns was demonstrated.

The optimal categorization and structure of items for each subscale of the BSIQ were cross-validated using the validation sample. In general, the patterns of categorization perceived by participants were consistent across the samples. Item parameter estimations across the samples were also stable and the hierarchical order of item difficulties was identical in both samples. Similar findings, the invariance feature of the Rasch analysis in estimating parameter measures, have been reported (Ewing et al., 2005; Zhu, 2002).

Evidence of construct validity using the Rasch calibrated person measures were provided. The mean person measures in logits for three BMI-based groups were compared for each subscale and contrasted to examine which groups significantly differenced. Generally, participants in higher BMI group tended to endorse lower categories in the body self-image satisfaction subscales and higher categories in the dissatisfaction subscales and vice versa.

Conclusions

Based on the findings from this study, two major conclusions can be drawn. The RSM provided advantages such as an effective and objective way to examine the categorization of the BSIQ and a solution to reduce linearity concerns by transforming ordinal data into logits. In regard to the research questions in the present study:

1. The BSIQ data fit the RSM in terms of fit statistics.
2. The RSM calibration adequately contrasts items and participants respectively according to their measures in logits.
3. The response categorization of the BSIQ is functioning as intended except for the FE, SD, HD, and II subscales. Combining the third and fourth categories results in the most acceptable fits for the FE, SD, and II subscales.
4. The Rasch categorization and item structure are stable and consistent across the samples.

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APPENDIX A

THE BODY SELF-IMAGE QUESTIONNAIRE

Response Format (Statement 1 through Statement 39)

Not at all True of Myself **(a)**	Slightly True of Myself **(b)**	About Halfway True of Myself **(c)**	Mostly True of Myself **(d)**	Completely True of Myself **(e)**

Statements

1) Controlling my level of body fat is important to me.
2) I've often wanted to be taller.
3) My overall fitness level is high.
4) My thoughts about my body depend on the clothes I'm wearing.
5) My naked body makes me feel sad.
6) I pay careful attention to my face and hair, so that I will look good.
7) I think my body looks fat in clothes.
8) I compare my body to people I'm close to (friends, relatives, etc.).
9) Having a well-proportioned body is important to me.
10) My naked body looks O.K.
11) Being around good-looking people makes me feel sad about my body.
12) I'm usually well-dressed.
13) My body is healthy.
14) Parts of my body are fat.

15) I'm more aware of my body when I'm in social situations.

16) Muscle definition is important to me.

17) I look good in clothes.

18) My body is fat overall.

19) My naked body makes me angry.

20) I spend time making my appearance more attractive.

21) My overall muscle tone is good.

22) I have large buttocks.

23) How well my body is functioning influences the way I feel about my body.

24) I care about how well-shaped my legs are.

25) I wish I were a different height.

26) My body looks good.

27) I feel depressed about my body.

28) My body is strong.

29) My body is overweight.

30) The way I feel about my body improves when I exercise regularly.

31) Body size matters to me.

32) My body is sexually appealing.

33) Most days I feel bad about my body.

34) I have an athletic build.

35) My stomach is flabby.

36) My body image is influenced by the state of my health.

37) My body is in shape.

38) If I were a different height, I'd like my body better.

39) I wish I were thinner.

APPENDIX B

FACTOR AND ITEM STRUCTURE OF THE BODY SELF-IMAGE QUESTIONNAIRE

Factor	Statement
Overall Appearance Evaluation (OAE)	10) My naked body looks O.K.
	17) I look good in clothes.
	26) My body looks good.
	32) My body is sexually appealing.
Fatness Evaluation (FE)	7) I think my body looks fat in clothes.
	14) Parts of my body are fat.
	18) My body is fat overall.
	22) I have large buttocks.
	29) My body is overweight.
	35) My stomach is flabby.
	39) I wish I were thinner.
Attention to Grooming (AG)	6) I pay careful attention to my face and hair, so that I will look good.
	12) I'm usually well-dressed.
	20) I spend time making my appearance more attractive.
Health/ Fitness Evaluation (HFE)	3) My overall fitness level is high.
	13) My body is healthy.
	21) My overall muscle tone is good.
	28) My body is strong.
	34) I have an athletic build.
	37) My body is in shape.
Health/ Fitness Influence (HFI)	23) How well my body is functioning influences the way I feel about my body.
	30) The way I feel about my body improves when I exercise regularly.
	36) My body image is influenced by the state of my health.

Factor	Statement
Social Dependence (SD)	4) My thoughts about my body depend on the clothes I'm wearing.
	8) I compare my body to people I'm close to (friends, relatives, etc.).
	15) I'm more aware of my body when I'm in social situations.
Height Dissatisfaction (HD)	2) I've often wanted to be taller.
	25) I wish I were a different height.
	38) If I were a different height, I'd like my body better.
Negative Affect (NA)	5) My naked body makes me feel sad.
	11) Being around good-looking people makes me feel sad about my body.
	19) My naked body makes me angry.
	27) I feel depressed about my body.
	33) Most days I feel bad about my body.
Investment in Ideals (II)	1) Controlling my level of body fat is important to me.
	9) Having a well-proportioned body is important to me.
	16) Muscle definition is important to me.
	24) I care about how well-shaped my legs are.
	31) Body size matters to me.