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A Description of an Application of the Rasch Latent Trait Model to the Student Version of the Jenkins Activity Survey

Karyn Holm Loyola University Chicago

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KARYN McGAGHIE HOLM

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AN APPLICATION OF THE RASCH LATENT TRAIT HODEL TO THE STUDENT VERSION OF THE JENKINS ACTIVITY SURVEY

By

Karyn Holm

A Dissertation Submitted to the Faculty of the Graduate School of Loyola University of Chicago in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

August

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The author, Karyn Holm, is the wife of Terrance A. Holm and the daughter of Robert and Kathryn McGaghie. She was born September 3, 1946 in Chicago, Illinois.

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CHAPTER·I

INTRODUCTION

Methodological research is necessary in order to create and improve measures of human behavior. Measurement of variables in the physical sciences has long been assumed to be more scientific than the measurement of variables in the behavioral sciences. Assigning numbers to tangible properties of variables in the physical sciences, explicitly demonstrates functional relationships or a direct correspondence between numbers and variables. However, quantification in the behavioral sciences has not been so easily achieved. This has been primarily due to the lack of specificity of relationships between observations and variables. Behavioral disciplines such as education and psychology are concerned with the measurement of constructs which may not be amenable to direct observation. This fact has fostered measurement which is somewhat arbitrary.

Latent trait theory describes a methodology to view the relationships of variables to a construct and to each other. This methodology is appropriate for applications to qualitative variables, so often important to educational and psychological research. Both latent trait models and factor analysis view the relationship between variables but the latent model approach, unlike the factor analytic approach, discriminates between latent rather than manifest data.

The evolution of latent trait theory can be traced to the

Social Science Research Council of 1941 which produced a monograph in which Louis Guttman discussed a need for dealing differently with qualitative variables, that is attribute variables with categorical manifest classifications, the basic form of which is the dichotomous variable (Lazarfeld and Henry, 1968). In addition, it was apparent that new mathematical models were needed for measuring qualitative data.

Latent trait models aim to measure phenomenon which cannot be directly observed. Individuals and objects can be placed along a continuum known as latent space with respect to an underlying trait or variable. The manifest observations must be indicative of variables related to the latent concept. Terminology important to latent trait theory is described by Lazarfeld and Henry (1968) and includes the following:

Latent variable: A variable for which there is not objective criterion.

Item: Maybe a question asked directly of an individual or it may be a certain characteristic of a respondent.

Probability notion: When A=yes and B=no, then the probability of A is equal to one and the probability of B is equal to zero. The probability range is from one to zero.

Latent space: The space occupied by the variable of interest. It is the space in which members of a population are located. The $P(A)$ or a positive response to any item in an item list is determined completely by position in this latent space.

Item traceline or item characteristic curve: A defining

function for each question which generates appropriate probabilities. For each point on the line there is a probability of a correct answer or positive response to any question.

A mathematical model which incorporates a probabilistic element is required to formalize the relationship of manifest data to latent data. The fundamental concepts of the general model include dimensionality of latent space, the axiom of local independence and the item traceline or item characteristic curve.

Latent trait models can differ according to the number of item parameters considered in the analysis of test items measuring a latent variable. A model can incorporate as many as three item parameters. These parameters are those of traditional item analysis procedures and include difficulty, discrimination and guessing.

The least complex latent trait model is the Rasch Model which is concerned with one item parameter. The Rasch Model assumes a common level of item discrimination and is concerned with item difficulty. This model considers person ability and item difficulty as being the only considerations necessary to determine the probability of a positive (correct) response to an item. In addition, the goal of instrument free and person free measurement are realized when items measuring a latent variable are defined and their position on the latent continuum is determined. The consequence of which is objective measurement of a latent variable.

Contemporary applications of the Rasch Model have been primarily concerned with relating the model to tests and test items already in existence. For example Rasch calibrations have been used on school

and military aptitude, achievement, and intelligence tests. Utilization of the model for banking of calibrated items to facilitate tailored testing and for detection of item bias are other current applications.

Relating the Rasch Model to items measuring personality and behavioral variables is relatively unexplored. Because the model seems to work for a variety of content areas, it is reasonable to demonstrate the feasibility of such an application. The questions proposed in the present study are related to the utility of a Rasch Model application to a testing instrument which purports to measure an operationally defined behavior, known as Pattern A or coronary prone behavior. This instrument, the Student Version of the Jenkins Activity Survey is used extensively to measure the behavioral component of heart disease. The Jenkins Survey has been used extensively in studies predicting heart disease. Positive outcomes resulting from a Rasch analysis will not only serve research and measurement methodology in general, but also assist to improve the Jenkins Survey by eliminating those items which are unnecessary and also by improving existing items.

CHAPTER II

REVIEW OF THE LITERATURE

Provision of a basis for study is enhanced by a literature review focusing on the following relevant, related areas. Included in this review are 1) Latent trait theory; 2) The one parameter latent trait model; 3) contemporary applications of the Rasch one parameter latent trait model; 4) other relevant applications of Latent Trait Theory; and 5) the measurement of Pattern A behavior.

Latent Trait Theory

The past decade has seen a shift in the techniques used to analyze test items from correlational approaches to estimation procedures provided by latent trait models. The conceptual definitions of the parameters associated with test items, namely difficulty, discrimination and guessing, are straightforward and easy to understand. Yet the utilization of latent trait models to arrive at one or more of these parameters requires mathematical sophistication (Baker, 1977).

Latent Trait Theory incorporates at least three underlying assumptions. These assumptions include local independence, latent space dimensionality and the item characteristic curve (Hambleton and Cook, 1977). The local independence assumption has both a strong and a weak interpretation. In its strong interpretation local independence means that the test item responses of a given subject are independent statistically. To be statistically independent requires that a subject's performance on one item does not affect performance on other items. Basically. this assumption is met when all test items measure

a single ability. A weaker interpretation of local independence differs from the strong interpretation only in terms of the strength of relationship between the variables (test items). When the strong interpretation of the local independence assumption is met, the probability of any subject's response pattern (l's and O's) is given by the product of probabilities for the obtained score on each item.

The local independence assumption is restrictive and may not always be satisfied. Lord and Novick (1968) state that local independence does not assume that test items do not correlate when a total group of subjects is considered. Whenever the subjects vary in the amount of the trait measured by the items, the outcome will be positive correlations between items. They further state that factor analysis can be used to determine local independence for an item set as there is equivalence between this assumption and the single dimension assumption.

Underlying the idea of the dimensionality of latent space is the assumption of unidimensionality. The number of dimensions occurring in latent space is dependent upon the number of traits being measured. Homogeneous test items are assumed to measure a single trait. This assumption may not prove true in the strict sense for most tests (Lord, 1968) but can be studied utilizing techniques of factor analysis (Hambleton and Traub, 1973). Factor analysis may be utilized to cluster interrelated items, making it possible to apply a selected latent trait model to each interrelated cluster.

The item characteristic curve also known as a trace line serves to mathematically relate the probability of success on each item to

the latent trait being measured. Each latent trait model has its own unique item characteristic curve, (Torgerson, 1958 and Lord and Novick, 1968), although each possesses the same general form. An item characteristic curve is a non-linear regression function of item score on the latent trait under consideration. A complete definition of an item characteristic curve requires that a general form be specified and parameters are known (Hambleton and Cook, 1977). Item parameters will depend upon the particular latent trait model being applied. The one parameter model focuses on the item difficulty parameter; the two parameter model focuses on both difficulty and discrimination while the three parameter model, in addition to difficulty and discrimination, includes a parameter for guessing. Gibson (1966) criticizes the three parameter model stating that many three parameter models would require two underlying dimensions in order to obtain adequate psychological meaning. Lord (1966) conversely states that the underlying ability (latent trait) is an ordered variable that can be viewed in a single dimension. In addition, the following restrictions are imposed on a test item: 1) the items are scored with a 0 or 1 ; 2) the raw score is the number of items answered correctly; and, 3) the items are homogeneous. Andersen (1977) supports these restrictions in his finding that when considering a questionnaire with two answer categories, a minimum sufficient statistic may be the raw score of number of correct responses.

An item characteristic curve depicts the probability of a positive response (scored as 1) to an item. It is important to note that the probability of an individual subject selecting a positive response

to an item is independent of the trait (ability) distribution in the population of individuals under consideration. Thus, the shape of the curve will be invariant across different samples of subjects. (Hambleton and Cook, 1977)

The One Parameter Latent Trait Model

The one parameter latent trait model is known as the Rasch Model as credit for its development is given to Georg Rasch (1966). The basic aim of his work was to develop probabilistic models, for which population could be ignored. Rasch's approach is unlike traditional approaches to psychological measurement, which link evaluation of a subject with a population by standardization of some kind. The one parameter Rasch Model is unique for it provides a sufficient estimator for person ability (latent trait) and does so using observable data (Wright, 1977). The model operates with two related assumptions. The first is that the unweighted sum of positively scored (correct) answers will contain all that is necessary to measure an individual. The second assumption is that the unweighted sum of positive scored (correct) answers given to an item contains sufficient information to calibrate the item (Wright, 1968; Rasch, 1966). The Rasch Model assumes all items have equal discriminating power and vary only in terms of difficulty. The difficulty parameter is depicted as δ_i for each item i and B_v represents the latent trait parameter (ability) for each person v. Both the difficulty parameter and latent trait parameter are used in the one parameter model to ascertain the probability of person v responding

positively to item i. The probability must remain between one and zero, but each parameter can vary from plus infinity to minus infinity (Wright, 1977). The Rasch probability for a right answer deals directly with this issue. The difference $B_v - \delta_i$ becomes the exponent of a base, signified in the following way: e $(B_v - \delta_i)$. This exponent becomes part of the ratio of the Rasch probability for a positive response $\overline{\smash{)}\{e(B_v - \delta_1) \mid 1 + e(B_v - \delta_1)\}}$. Thus, the probability of a positive response (P_{vi}) is dependent upon the difference between item difficulty and the amount of a latent variable possessed by the individual. To offer further clarification, the more person v's latent trait (ability) exceeds the item's latent trait (ability) requirement, the greater the positive difference and consequently, the greater the probability of a positive response. The reverse is also true, as when the amount of latent trait of the individual is less than that required by the item, the probability of a positive response is less than .5. In this situation, the difference between B_v and δ_i is a negative one.

The general mathematical unit of the Rasch Model is the "logit". The amount of an individual's latent trait (ability) consists of the natural log odds for a positive response to items chosen to define the scale origin. The following equations illustrate the probabilities for a positive (success on an item) response.

Probability for a positive response:

$$
e^{B}/(1 + e^{B})
$$

The positive response odds:

 $P/(1 - P) = e^{B*}$

*The natural log is B.

As with the probability for a positive response, the probability of a negative (failure) response is concerned with the natural log odds for a negative (failure) response on the item in question.

The equation depicting this probability as well as the negative response odds for an individual at $B=0$ of succeeding on a difficult item is:

 $e^{-\delta}$ /1 + $e^{-\delta}$

The odds for a negative response of failure is given as:

 $(1 - P)/P = e^{-\delta t}$

*the natural log is δ

The difference between the amount of ability (the latent trait) and item difficulty (intensity) is $B - \delta$ and governs the probability of a correct (positive) response. Because it is this difference which influences the probability of a correct (positive) response, any constant can be added or subtracted without influencing the weight of the difference on the probability of success. Thus, the zero point of the latent variable is arbitrary. The zero point can be placed at the easiest item or at least able individual (the individual possessing the least amount of the latent trait); at the mean difficulty or the mean intensity of calibrated items; or can be placed so negatives do not occur (Wright, 1977). The item characteristic curves for the one parameter Rasch Model do not intersect. They differ only along the ability (latent trait) scale.

The proportion of wrong or negative answers is bound by the calibrating sample, the expansion factor (the sample spread coefficient) and the sample ability level which corrects this sample binding.

The result is an item difficulty (intensity) estimate free from any influences of mean ability or variance of the calibrating sample (Wright, 1977).

Sources of item bias may exist as terminology may be unfamiliar to some individuals or the terms may not bear directly on the ability (latent trait) being measured. But statistical detection of item bias can be made using Rasch residuals (Wright, Mead, Draba, 1976).

The one parameter Rasch Model does not have a discrimination or guessing parameter. Wright (1977) states that it is never certain if the discrimination parameter can be reliably estimated as the discrimination values are sensitive to the distribution of person abilities in the sample used for calibration. A related problem is that when iterative solutions to estimation are used, they tend to diverge at the extremes. In reference to the guessing parameter it is a known fact that its estimation requires either extremely large widely spaced samples (for items) or very long tests (for individuals).

The advantages and disadvantages of latent trait models are reviewed by Hambleton et al (1978). They state that the most important advantage these models have is that an individual's ability can be estimated independently from the particular choice or number of items. Once items are calibrated, individuals can be compared with each other even though they may have been tested with different items. The disadvantages are related to robustness of the models or the degree to which the data can deviate from underlying assumptions and to the numerical problems arising from the estimation equations which are associated with the convergence of the algorithms. Convergence is not

an issue with the Rasch One Parameter Model but is with the two or three parameter models, which require extensive computer time, large numbers of items and large numbers of subjects.

When compared to the Birnbaum 2 parameter model, the lack of the item discrimination parameter in the Rasch Model does not result in poorer calibration in the presence of varying item discrimination according to Dinero and Haertel (1977). They further stated that until it is shown to be either inadequate or inferior to another model, the Rasch Model, being the simplest latent trait model, should be the model of choice,if only on the basis of mathematical elegance.

The real advantage of the Rasch One Parameter Model will not be apparent until the technology of trait measurement becomes more sophisticated. But Anderson (1972, 1973) found the one parameter model to possess unbiased, consistent, efficient and sufficient estimates for both ability (latent trait) and difficulty parameters. The model is not without criticisms. Whitely and Davis (1974) see difficulties such as a measurement yield which is less than objective; item invariance only under certain conditions; and lack of precision in equivalent test forms. Answers to their criticisms are provided by Wright (1977) who demonstrates these criticisms were due to misconception and not to problems in the model itself.

Application of One Parameter Rasch Latent Trait Model

Sample free item analysis (Wright and Panchapakesan, 1969) has as its basis the Rasch Model which says that when an individual encounters any test item the outcome is influenced only by the product

of the ability of the person and the easiness of the item. Thus, the only characteristic upon which items differ is ease of response. The model assumes that all the items used on a measuring instrument measure the same trait. Items will not fit together if they measure different abilities. Wright and Panchapakesan describe fit to the model, as not only implying that item discriminations are uniform and substantial, but that guessing and item scoring error are not influential. Holding to the criterion of fit to the model enables bad items to be deleted. The second phase of sample free item analysis involves person measurement. In this phase, some or all of the calibrated items are used to obtain a test score. In addition, an estimate can be made of person ability. A standard error of this estimate is made from the score and from the easiness of the items used. The standard error of the ability estimate is a measure of precision and depends on the number of items.

Wright and Douglas (1977) compare the Wright-Panchapkesan procedure termed the unconditional solution, UCON, with Anderson's (1972) conditional procedure. Although the UCON solution is biased, it should be used when more than 30 items are analyzed. To lessen the bias, a correction factor is demonstrated. Mead (1976) worked with fitting data to the Rasch Model after item difficulties and person abilities are estimated. His focus was primarily analysis of residuals.

The Anchor Test Study was re-evaluated (Rentz and Bashaw, 1977) using Rasch Model procedures. The outcome was a new scale to be known as the National Reference Scale (NRS) for reading. The NRS consists of 28 reading tests which can be used interchangeably. The Rasch Model provided the means for equating the tests. In addition, all of

the items on all of the tests were calibrated, 2,644 in number, to enable a user to estimate a NRS score {rom any subset of items. Another application was that of obtaining test free ability estimates (Linsley and Davis, 1977). It was found that raw score ability estimates seem to be influenced by the difficulty of the items used in measurement but that the Rasch ability estimates seem to be independent from item difficulty.

It is of interest to note that applications of the Rasch Hodel are at present moving into analysis of attitude and personality data, not being limited to only ability estimates. Andrich of the University of Western Australia (1975) writes of applying the Rasch Model to attitude data. Related to this work is that of Doenges and Scheiler (1977) who demonstrated that practicality of a latent trait approach to scaling the Rorschach. They began with the assumption that scaling Rorschach items may be more amenable to a probabilistic rather than a deterministic model. Regularities postulated by the probabilistic latent trait model were found to be true for three Rorschach variables. Another application of the Rasch Model to a behavioral instrument involved the Marke-Nyman Temperament Scale (Becket al, 1978). It was demonstrated that a subscale for each of the three previously defined personality measures existed even when administered to different groups of subjects.

Scaling Applications of Latent Trait Theory

Inferring a latent scale of values when the observed phenomenon are choices on a set of comparisons was an issue addressed by Luce

(1959). The basic ideas behind Luce's work include an individual's subjective probability of events and their subjective value to him. What he demonstrated was that the probability of choosing one of a pair of alternatives is dependent upon the difference between the scale values of the two alternatives.

An attempt made to utilize a binomial logistic latent trait model in the study of Likert-style attitude questionnaires found that an advantage in this application is that the model can be useful in determining if the middle category on a Likert scale functions as a neutral category (Andrich, 1978). It was demonstrated that to function effectively, the neutral category should be neither under or over represented. The finding based upon analysis of a Likert style questionnaire administered to 309 fifth year school children in Australia, was the proportion of subjects responding in the undesirable category for three select items was considerably less than the probability indicated by the model. Thus, the middle category was shown not to function as expected.

A simple method for estimating parameter values for the normal ogive or logistic latent trait mental test model is outlined by Jensema (1976). This method is compared to the traditional maximum likelihood method in terms of the influence of sample size and true item parameter values. Jensema found that obtaining maximum likelihood parameters for both discrimination and difficulty will be more difficult if the discrimination of the items is great; the number of items in the data set is small and if the sample size is small. In addition, the computer time required for maximum likelihood estimations increases not only with the number of items and subjects but also with an increase in item discrimination which is related to mathematical characteristics.

Better procedures of developing vertically equated tests to cover wider ranges of difficulty is a contemporary testing issue. The Rasch Model was found to be an adequate procedure (Slinde; Linn, 1978) to achieve this goal. The particular appeal of the Rasch Model being the properties of person-free test calibration, namely that estimated item parameters are invariant for all groups of persons and item-free person measurement which means that the same measure would be obtained for a person with calibrated items irregardless of what subset of items is used.

Measurement of Pattern A Behavior

As early as the 1940's psychoanalytic journals described a coronary character (Arlow, 1945) as being an individual possessing pseudo-masculine identifications. In addition, Arlow stated that the most striking behavioral features of this person were a passionate urge for very hard work; a burning ambition and tendency to dominate others; and vascilating between independence activity and dependence inactivity. The motor activity which is manifested in hard work provides the primary outlet for aggressive feelings (Van Heijningen and Treurniet, 1966).

Elevated blood pressure, elevated serum cholestorol and smoking are the three most firmly established cardiovascular risk factors. Psychosocial influences have been demonstrated to constitute a causal and modifiable coronary heart disease risk factor (Epstein, 1979). The follow-up to the Framingham study which covered a span of 18 years clearly demonstrated the predictive value of Pattern A behavior in the development of Coronary Heart Disease (Haynes, Feinleib and Kannel, 1978). This reinforced the 1976 report of Brand, Rosenman, Scholtz and Friedman which cited the importance of Pattern A in reference to coronary heart disease.

way: Rosenman (1966) describes Pattern A behavior in the following

Pattern A appears to be a particular action emotion complex which is exhibited by an individual who is engaged in a relatively chronic and excessive struggle to obtain an obsessive number of things from his environment in too short a period of time, or against opposing efforts of other persons or things in the same environment.

Thus, being overly competitive, ambitious, hard driving and time conscious are all typical Pattern A behaviors. Pattern B behaviors are described as being opposite to Pattern A.

Pattern A behavior has been shown to be associated with coronary heart disease. Individuals demonstrating extreme manifestations of Pattern A behavior possess signs indicative of coronary heart disease such as elevated blood cholesterol, elevated blood triglycerides and diurnal norepinephrine secretion (Rosenman and Friedman,1963). Recently, Jenkins (1974) reported twice the incidence of new coronary artery disease among men classified as Pattern A.

Syme (1975), upon review of the social and psychological components of coronary heart disease, expresses the positive aspects of a straight-forward classification of people into a Type A behavior

pattern in order to predict heart disease independently from other risk factors. At the present time, further work is needed to develop and refine measures of coronary prone behavior.

Two commonly used approaches to the measurement of Pattern A behavior are the Standardized Stress Interview, and the Jenkins Activity Survey. The Jenkins Activity Survey exists in two forms, an adult version and a student version.

The Standardized Stress Interview developed by Friedman and Rosenman(l964) assists to identify not only the content of a subject's response but also the overt behaviors. A four point rating scale is utilized to determine if the behavior in question is either completely or incompletely developed. The rationale behind the Standardized Stress Interview is that overt Pattern A behavior is made visible when the subject is responding to topics which are threatening or to important concerns in his life. The issues presented by the interviewer focus on the intensity of the subject's ambitions, his degree of competitiveness, and his sense of time urgency. In addition, a portion of the interview is directed toward the nature and extent of hostile feelings. This approach to measuring Pattern A behavior necessitates the use of trained supervisors to afford consistency of outcome.

Reliability of the Stress Interview is said to be comparable to the reliability of the medical diagnosis (Jenkins et al, 1968). The degree of agreement of two trained judges in one study (Jenkins, Rosenman and Friedman,l968) was found to be 84%, when the judges rated the behavior patterns of the 75 cases studied in the same way 84% of the time. Other studies (Caffrey, 1968; Keith, Lown, and Store, 1965;

Friedman, 1968) were in agreement, citing inter rater reliabilities of 75-84%. Test-retest reliability was found to be (Jenkins et al, 1968) 80% in a sample of 1064 males.

Another measure of the Type A Behavior Pattern is the Jenkins Activity Survey for Health Prediction (JAS). It is an objective selfadministered questionnaire developed by C. David Jenkins of Boston University Medical School (1967). The JAS provides continuous scores on the A-B dimension. A series of optimal weights derived from discriminant function equations provide the basis for scoring of the JAS items. Positive scores denote the Pattern A direction and negative scores the Pattern B direction. Zyzanski and Jenkins (1970) demonstrated the existence of three orthogonal factors correlated with the overall A-B score. The identification of the above three factors were consistent with earlier work which made these assumptions on a clinical basis. The names given to the three factor scales are (S) Speed and Impatience, (H) Hard Driving, and (J) Job Involvement. The test-retest reliability of the JAS determined by Jenkins (1971) was based upon a separation interval of one year and was found to be .66. In another study (Jenkins et al, 1974) based upon a four year separation interval found less than a 10 point difference in A-B scores.

Literature Review Summary

The underlying assumptions of latent trait theory include local independence, latent space dimensionality and the item characteristic curve. These assumptions may be met in varying degrees by different tests but hold true for all latent trait models. The latent trait

models currently in use estimate from one to three parameters. The parameters include difficulty, discrimination and guessing.

The one parameter latent trait model known as the Rasch Model provides a sufficient estimate for person ability (latent trait) and does so using observable data. The Rasch Model assumes all items have equal discriminating power and vary only in difficulty. Because a sample spread coefficient can be calculated, the item difficulty is free from variance or mean ability of the calibrating sample.

The one parameter Rasch Model has been used for test item analysis and securing ability estimates for individuals on tests of ability and achievement. Tailored testing, a consequence of item banks containing calibrated items, is at present receiving considerable attention. In addition, there is beginning interest in the utilization of the Rasch Model for analysis of attitude data. Other latent trait models have been used with attitude data as for example, the binomial logistic latent trait model in the study of Likert style attitude questionnaires.

Assessment of the existence of Pattern A behavior in an individual becomes increasingly important after examining the research describing the influence of Pattern A behavior on coronary heart disease, a major health problem in the United States. It has been demonstrated that those individuals who are assessed either by interview or by questionnaire to exhibit Pattern A behavior tend to demonstrate a high incidence of coronary heart disease. Demonstration of this phenomenon in repeated studies has resulted in increased certainty that behavior and coronary disease seem to be related. A consequence of this has been a striving for a greater theoretical understanding of Pattern A behavior

with only secondary interest in the psychometric properties of the measuring instruments themselves. Yet, significant research findings are directly related to the quality of data collection instruments. The increased objectivity which has been afforded by the Rasch Model applications to achievement, aptitude and intelligence tests is also a desirable goal for testing instruments such as the Student Version of the Jenkins Activity Survey.

CHAPTER III

METHOD

Introduction

The following methodology was designed to investigate an application of the Rasch Latent Trait Model to the Student Version of the Jenkins Activity Survey. The feasibility of utilizing the Rasch Model to improve this measure of Pattern A behavior was explored.

Statement of the Problem

The primary purpose of this study was to describe an application of the Rasch Latent Trait Model to the 21 items contained on the Student Version of the Jenkins Activity Survey, a measure of Pattern A behavior. The results of the Rasch Model application were compared to the results of a Guttman Scaling procedure. Of primary concern was to determine if the Rasch Model could be utilized to create a Guttman like scale. Secondary benefits of this analysis included: investigation of the characteristics of the 21 Jenkins items as well as suggestions for item and instrument improvement.

In order to accomplish the foregoing purpose, the following problems were addressed.

Problems

Will the 21 items contained on the Student Version of the Jenkins Activity Survey fit the Rasch Latent Trait Model?

How will the 21 items contained on the Student Version of the Jenkins Activity Survey order in degree of intensity as a result of this Rasch Model application?

How will the ordering of items accomplished with the Rasch Hodel compare to the item ordering of a Guttman Scaling procedure?

Study Design

A descriptive research design was employed to structure the investigation. This represented a previously unexplored Rasch Model application. The outcome of each research problem was analyzed in detail. Included within this framework were probable explanations for these outcomes. What was demonstrated in this study can direct further applications of the Rasch Model, not only to the Student Version of the Jenkins Activity Survey, but other attitude and behavioral questionnaires as well.

Subjects

Rationale for subject selection. Student subjects were included in this study who consented to participate. The initial encounter with potential subjects was marked by an explanation of the purpose of the study. The Human Investigation Committee of Rush University, Chicago, Illinois, where the majority of subjects were enrolled, determined that a written consent was not required. This decision was based upon the fact that subjects were not asked for specific identifying information and would be directed only to check their responses to items on the Jenkins questionnaire. Consent to participate was thus, verbal agreement. In addition, failure to complete the questionnaire was also considered nonagreement.

A provision for randomization was not included. A nonrandom approach to subject selection was based upon the fact that the item characteristic curve of the Rasch Model is not dependent upon the distribution of the latent variable, in this case, Pattern A behavior, in the subject population. The shape of the curve is invariant across different groups of subjects from the defined population which was in this study, college students.

Subject characteristics. The total number of subjects included in the study was two hundred-eighty seven (287). These student subjects were obtained from intact classrooms at Rush University, Chicago, Illinois (N=250) and Thornton Community College, South Holland, Illinois (N=37). All of the students were involved in health career studies which included medicine, nursing, and clinical nutrition. The demographic variables of interest (See Table 1) were: year of college study; sex; and the presence of coronary risk factors. Coronary risk factor information was collected because of the supposed relationship between Pattern A behavior and coronary heart disease. The number of undergraduate students was 198, while 89 were graduate students. There were approximately twice as many females $(N=188)$ as there were males (N=99). It was interesting to note that one third of the students indicated that there was a history of heart disease in their family; almost one third of the students were overweight; and that almost one-sixth of the students were smokers. Diabetes and high blood pressure occurred with less frequency with 60 of the 287 subjects indicating they were diabetic and 31 indicating they were told they had high blood pressure.

Table 1

NUMERICAL DESCRIPTION OF SUBJECTS ACCORDING TO DEMOGRAPHIC VARIABLES (N=287)

Year of College Studies 198 Undergraduate Students 89 Graduate Students Sex 188 Females 99 Males High Blood Pressure 31 Yes 256 No Smoking 48 Yes 239 No Diabetes 60 Yes 227 No Weight 79 Overweight 28 Underweight 180 Average Weight Family History of Heart Disease 99 Yes 188 No
Instrumentation

The Jenkins Activity Survey was modified into a student version. Items in the original instrument relating to job and income were either eliminated or modified to coincide with a student's lifestyle. For example, the item in the adult version reading "How often are there deadlines on your job?" was changed to read "How often are there deadlines in your courses?" The student JAS consists of 21 items which are scored rendering a Pattern A response a value of 1 and Pattern B response a value of zero. Thus 21 becomes the maximum A score and 0 becomes the maximum B score. It was found (Glass, 1974) that the median A-B response for college males in Texas was between seven and eight. Subjects scoring above this median were designated as Pattern A and those below, Pattern B.

The reliability of the student JAS was determined in an informal manner. Records were kept on the stability of the scores of those subjects who were administered the instrument a second time. The rationale for the absence of a more systematic approach to the determination of reliability was the similarity of the adult and student versions. Factor analysis of the student JAS yielded two factors (Glass, 1974) which corresponded to the H and S factors demonstrated by Zyzanski and Jenkins (1970). These results were based upon the responses of 459 male college students.

Administration of the Student Version of the Jenkins Activity Survey. The administration of this questionnaire involved the following considerations. First of all the expectation was verbalized that each participant would answer the questionnaire honestly. This

expectation was also included on the written instructions. The student subjects were also asked to answer each question as indicated. The questionnaire was administered under time limited conditions described by Nunnally (1967) as occurring when subjects are given a set amount of time to complete an entire test. It was reasonable to assume that the time spent on a specific item varied from subject to subject.

Procedure

Introduction to data analysis. The Rasch Latent Trait Model was used to analyze the data. It was assumed that Pattern A behavior is an ordered variable which can be represented numerically in a single dimension. The subjects were assumed to exist on a linear continuum in such a way that the amount of Pattern A behavior could be represented quantitatively by the subject's position on the continuum. The 21 items were also assumed to exist on a linear continuum in such a way that the amount of Pattern A behavior measured for each item could be represented quantitatively by the item's position on the continuum.

The instrument in question, the student JAS-SV measures two latent classes which will be referred to as K_1 and K_2 . The responses to each of the 21 items were scored as dichotomous items with a Pattern A response being equal to one and Pattern B equal to zero. The accounting equation depicting a positive response to Item A is depicted as follows: $P(K_1)$ x $P(A_1K_1) + P(K_2)$ x (A_1/K_2) .

The P(K₁) is the probability of belonging to class 1. The P(A₁/K₁) is the probability of giving a positive response to A given that the respondent belongs to class 1. An equation such as that depicted above can be generated for each of the 21 items. The equation expressed in the general form is as follows where $P(X_1)$ is the probability of a positive response to item X: $P(X_1 = \Sigma P(K_1) \times P(X_1/K_1)$.

Preparation for analysis. Data collection procedures involved the administration of the Student Version of the Jenkins Activity Survey (JAS-SV), consisting of 21 items which are said to measure Type A (Coronary Prone Behavior). The 21 items were scored dichotomously with a one representing a Type A response and a 0 representing a Type B response. Seven additional items were added to the original instrument to obtain demographic and coronary risk factor information from each subject. Two of the seven items concerned year of college study and sex respectively while the remaining five items focused on high blood pressure, cigarette smoking, diabetes, body weight and family history of heart disease. These five additional items were constructed so that a positive response would indicate the presence of a coronary risk factor and could be given a point value or score of one.

To prepare the data for analysis the 21 items were given variable labels. Contained in Appendix E is each item and its respective label. Item 1 which addresses the presence of problems in everyday life was named LIFE while Item 2 which asks how an individual behaves under pressure or stress was designated STRE. The third and fourth items, both of which involve eating speed, were

called EAT 1 and EAT 2 respectively. LIST was the label given to Item 5 which involves an individual's ability to listen to another. Item 6 involves putting words in another's mouth to speed up conversation, thus was termed WORD. The seventh item asks how often an individual is late for a meeting and became the variable LATE. DRIV, COMP, COMP 2 became the names for items 8, 9, and 10 all of which address harddriving and competitive behavior. The activity level and energy (items 11 and 12) questions were named ACTI and ENER. The issue of temperament is addressed by items 13 and became the variable TEMP. Meeting deadlines (items 13 and 14) whether imposed by others or by one's self were the items labeled TUIE and TIM2. Item 16 involving focusing on 2 projects at the same time became the PROJ variable. SCDL was the name given to the next item (number 17). SCDL asks the subject whether he or she maintains a regular study schedule over vacations. The frequency of bringing work home at night is asked in item 18 which became the variable WORK. Leadership, responsibility and seriousness of approach to life are addressed in the remaining 3 items of the JAS-SV (items 19, 20, and 21). Variable labels given to items 24 through 28 which asked the respondent to indicate the presence of coronary risk factors were as follows: item 24 HIBP (high blood pressure); item 25 SMOK (smoking); item 26 DIAB (diabetes); item 27 WElT (overweight) and item 28 HIST (family history of heart disease). Items 22 and 23 asked year of college studies and sex respectively; these items were used for demographic purposes and were not given variable names.

Sequence of the Rasch Model Application. Evaluation of the statistical fit of the Jenkins items involved the following steps.

(The specific detail surrounding each step is given in Appendix B and Appendix C):

- 1. The residuals were calculated in the data from the values expected from the model.
- 2. The residuals were examined to determine if they were acceptable or unacceptable. Criteria for an acceptable residual was a mean square of one.

Item calibration was accomplished in the proceeding manner. Appendix contains the specific details of manual item calibration.

- 1. Items were calibrated on the latent variable.
- 2. Sample free item calibration was obtained. An adjustment was made using a Rasch difficulty estimate (Wright, 1977) for the influence of sample ability. $d_i = M + Y \ln |\overline{(N - s_i)}/s_i|$

Where $N =$ number of individuals attempting the item

- $M = an$ expansion factor
- $Y = (1 + \frac{v}{2.89})^{\frac{1}{2}}$
- $v = ability variance$
- d_i = item difficulty (intensity)

This adjustment estimates item difficulty (intensity) as being equal to the average ability (latent trait) of the individuals sampled in conjunction with a sample spread adjustment multiplied by the log adds for wrong (negative responses to the item).

Description of BICAL Version 3. BICAL Version 3 was the computer program utilized for this Rasch Model application (Mead, Wright, Bell, 1979). An assumption of the Rasch One parameter Latent Trait Model is

that items which are less intense (difficult) should be answered positively not only by those with high ability but by those with lower abilities as well. In addition, a more intense item should be answered positively only by those individuals who are more able, and who possess a greater amount of the variable being measured.

BICAL VERSION 3 (See Appendix F) allows division of the calibration sample into subgroups by score level. The N GROUP parameter allows for control of the number in each group. The best fitting items should demonstrate progression across ability subgroups. That is *^a* greater proportion of those individuals in the higher ability groups should get the item correct. Thus, as an item moves across ability subgroups evidence of an increasing proportion of positive responses should be apparent. An item's progression across subgroups allows assessment of item difficulty invariance. Failure of an item to function in this way may be due to *a* problem with the item or *a* problem with the persons in the calibrating sample. An item may not be clearly differentiated among the designated ability subgroups, but demonstrate differentiation of less than the number of subgroups predetermined by the N GROUP parameter. For this situation to occur, some of the ability subgroups will demonstrate a similar proportion correct. A similar proportion correct is defined as a standard error or less between ability groups. To offer an example, consider an item which demonstrates *a* similar proportion correct for groups 1, 2 and 3 but progresses as the model predicts for ability subgroups 4, 5 and 6. This particular item divides the calibrating sample into 4 ability subgroups rather than a predetermined 6.

Another situation which may occur is that in which lower ability groups get a higher proportion correct (positive responses) than higher ability groups. This item is not functioning as the model would have it function and should be examined for clarity and content. A particular item may be victim to yet another problematic situation in which the proportion of positive responses demonstrates sporadic progression. In this case, the item in question may show some of the progression expected by the model but may demonstrate a lower proportion of positive responses for a proceeding ability subgroup. This may occur just once or 2-3 times. To gain insight into why this may have occurred, individual response patterns should be examined for plausibility, e.g., to determine if less able persons answered a more intense item positively or if more able persons failed a seemingly less intense item. In summary, the item characteristic curves should become larger as there is movement from left to right across latent variable subgroups, e.g., from the less able to the more able persons.

The item fit statistics of BICAL VERSION 3 include: item fit between groups; a total t-test; a weighted mean square; a discrimination index and point biserial correlation. The fit statistics are mean square standardized residuals. These standardized residuals consider item by person responses which are averaged over persons (Wright and Stone, 1978). A traditional approach to partitioning of the total fit test into the fit between ability subgroups and the fit within the ability subgroups is used. The number 1 is used as the reference value. As a mean square residual becomes greater than 1, the obtained item characteristics curve will increasingly deviate from the Rasch Model expectations. This occurs in either of the following situations: 1) when too many persons of high ability fail an easy (less intense) item or, 2) when too many persons of low ability respond positively to a difficult (more intense) item.

The between group fit statistic accounts for each ability subgroup's contribution to the curve of each item. This allows for an evaluation of the extent to which the item characteristic curves which would be expected by the Rasch Model are in agreement with the item characteristic curves which are obtained with the responses of the calibrating sample.

The total fit t-test considers the responses of the entire calibrating sample. The test of total fit addresses the general agreement between all items which are said to define the variable and the particular item in question. As is the case with the between group fit statistic, the value obtained becomes greater than one as the responses to the items deviate from the responses expected by the Rasch Model. The events which are dissonant to the model occur when either high ability persons (those individuals possessing greater amounts of the trait being measured) answer an easier item (less intense item) negatively or when low ability persons (those individuals characterized by the model as possessing lesser amounts of the variable being measured) respond to a difficult item (more intense item) with a positive response. Thus, when an item does not depart significantly from the Rasch Model, the mean square residuals will manifest a value close to one. Determination of the statistical significance of large mean square values can be accomplished by

comparing the value obtained with the expected standard error.

The index of discrimination represents the trend of departure from the model in linear terms. Here again the reference value is one. A discrimination index close to one signifies that the observed and expected item characteristic curves are in close approximation. An item which may have failed to differentiate between high and low ability persons will have an index of discrimination less than one and be represented by a flat item characteristic curve. There also may be items which give the appearance of discriminating better than most other items. Indexes of greater than one will represent these items. Unusually high discrimination indexes should be investigated for local interaction and item over-fit. Local interaction may be the result of a secondary characteristic of the item or of the sample. Secondary characteristics of either items or people may produce local interaction. Secondary item characteristics may include presence of a response set, or an ambiguous question.

While secondary people characteristics encompass sources of people variation such as sex, previous experiences, the term "overfit" refers to the situation in which an item is calibrated as being relatively easy (less intense) item but produces a discrimination index of greater magnitude than a more difficult (more intense) item. The problem with this overfit is that the particular item doesn't demonstrate the irregularities that the Rasch Model tolerates. Those individuals possessing more of the latent variable (smarter individuals) never answer the item with a negatively scored response, while the model says that some individuals should do so.

The point biserial correlation coefficient provides traditional item information which can be compared to the Rasch BICAL **111** output. The point biserial coefficient demonstrates the relationship between a continuous variable and a categorical variable. Thus, the reported point biserial correlation coefficient represents the relationship between total score and the dichotomously scored item.

Description of the Guttman Scaling Model. A Guttman Scale is a deterministic scaling model, unlike the Rasch Model which is probabilistic in nature. The presence of a Guttman Scale is derived by determining if the data fit a triangular response pattern as depicted on Table 2. A set of items which produces a pattern of responses which approximates this triangular pattern is said to constitute a Guttman Scale. The issue in Guttman Scale Analysis is to find that set of items which approximates the triangular deterministic model pattern. Torgerson (1958) presents methods for deriving a triangular response pattern each of which necessitates not only negating some items but finding the best possible ordering of items and people.

Guttman Scaling is commonly known as scalogram analysis or cumulative scaling. Guttman (1944) created this method of scaling for the purpose of determining whether statements used in the measure of some attitudinal trait are unidimensional. Another characteristic of Guttman Scales is that they are cumulative. This cumulative characteristic allows the items contained on an instrument to be ordered by degree of difficulty. Thus the assumption is that an individual subject who answers yes or positively to a difficult item will always respond positively to a less difficult item. Guttman originally

Table 2

TRIANGULAR RESPONSE PATTERN

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recommended that 10-12 statements be administered to not less than 100 individuals. When his scaling technique is applied certain items are designated as scalable and are included in the new instrument. Those items not scalable are not included.

Many advantages are afforded by Guttman's approach (Black, 1976). These advantages include: demonstration of the unidimensionality of items; an individual's total response pattern can be reproduced when his/her total score is known; and because the assumption of a scalable set of items is made, individual response inconsistencies can be identified.

The Guttman approach is not without disadvantages. A major disadvantage is that when a large number of items is used with a large number of subjects the procedure becomes cumberson without the assistance of a computer program.

Guttman Scale Computer Program Application. A Guttman Scale Computer Program (SPSS, 1975) was applied to the responses of the 287 persons to the 21 item Student Version of the Jenkins Activity Survey. The 10 most intense items as defined by the Rasch Model calibration were to define a Guttman Scale to be known as Type A3. This Guttman Scale computer program specifies that 12 variables be the maximum number of variables used to define a Guttman Scale. Therefore, the decision was made to compare the most intense items as defined by the Rasch Model. The most intense items were assumed to be the best indicators or measures of Pattern A behavior.

This Guttman Scaling computer program has as its basis, procedures developed by Anderson and Goodenough (1966).

The item ordering can be automatically determined by this program. This is done by considering the percentage of subjects who fail or reject each of the items. Statistics helpful in evaluating the sealing results are available.

The Guttman Scale computer output yields the following information: the percent of respondents passing and failing each item; an item-by-item accumulation of errors, the number of respondents failing an item when they should have passed it and the number of respondents passing an item when they should have failed it; and a coefficient of reproducibility which measures the extent to which a subject's scale score is predictive of his/her response pattern. The coefficient of reproducibility is illustrated by the formula from which it is derived.

COEFFICIENT OF REPRODUCIBILITY = $1 - TOTAL$ # OF ERRORS TOTAL # OF RESPONSES

In addition a minimum marginal reproducibility, a percent improvement, a coefficient of scalability and interitem correlations are also reported. The minimum marginal reproducibility gives information concerning the smallest coefficient of reproducibility that could have occurred for the scale, given the specified cutting points as well as the number of subjects both passing and failing an item; (it 'should be noted that the difference between the (1) coefficient of reproducibility and the (2) minimal marginal reproducibility is the extent to which the coefficient of reproducibility is due to response patterns and not to the cumulative interrelationships

of variables.); the percent improvement reflects this difference and the coefficient of scalability which is a ratio gained by dividing the percent improvement by the difference between a value of 1 and the minimum marginal reproducibility. The interitem correlations are reflected by Yules Q and biserial correlations which may assist to identify specific items not related to any other item.

The value range attributed to the coefficient of reproducibility is from zero to one with an acceptable value generally said to be a value of .9 or greater. A value less than .9 is said to reflect an invalid scale. The coefficient of scalability also ranges in value from zero to one but differes from the reproducibility coefficient in what is said to be the acceptable value. When a scale is unidimensional and cumulative in the Guttman sense, scalability should be represented by *a* value of .6 or above.

RESULTS

Introduction to the Results

The results of the data analysis are presented to provide a response to each research question. The primary considerations were: to evaluate the statistical fit of the 21 items contained on the Student Version of the Jenkins Activity Survey to the Rasch One Parameter Latent Trait Model; to determine how these 21 Jenkins items would order in degree of intensity and to compare this Rasch Model application to the application of a Guttman Scaling procedure.

For purposes of this analysis the difficulty parameter of the Rasch Model was designated as intensity while the ability parameter was described as the amount of the latent variable possessed by the subjects. The assumed latent variable measured by the Jenkins is Pattern A behavior. These differentiations were made in order to avoid confusing this application of a behavioral measure with the usual achievement and ability test applications of the Rasch Model. In addition this terminology seemed more amenable with the intent of this descriptive analysis namely to determine if the Rasch Model may be used to create a scale in the Guttman sense.

Rasch Fit Analysis

The first question proposed in this study was: Will the 21 dichotomously scored items contained on the Student Version of the Jenkins Activity Survey fit the Rasch Model?

General item and subject information were considered prior to

specific item fit analysis. Table 3 depicts the response frequencies for each item. A score of one denotes a positive response. It was of interest to note that item 18, the variable WORK, received the largest number of positive responses (247 positive responses) while item 17, the variable SCDL received the least number of positive responses (15 positive responses). Other items displaying a great number of positive responses included item 1, the variable LIFE; item 3, the variable LATE; item 8, the variable DRIV; items 9, 10, COMP and COM2; item 13, the variable TEMP; and item 15, the TIM2 variable. It was reasonable to assume that those items receiving many positive responses would be designated as being the least intense, while those items were few position (Type A) responses would attain a higher level of intensity.

Rasch scores which were converted to person ability (amount of Pattern A behavior) in logits are included in Table 4. The highest raw score received by any subject was 18 which when converted to 1ogits is 2.07. The lowest possible score was a score of 1, received by 3 persons. Converting a score of 1 to log ability results in a value of -3.35 . Thus, the range of person ability in logs was -3.35 to $+2.07$. The mean person ability was $-.52$ with a standard deviation of .70. Placement of person ability in logs along the x, y axis produced the test characteristic curve (TCC) displayed in Figure One. The TCC produced by the 21 item Jenkins administered to 287 subjects procuded an ogive curve which appeared to be in accordance with the Rasch Model.

Consideration of the ogive curves for each item, namely the 21

Table 3

ALTERNATIVE RESPONSE FREQUENCIES

JENKINS ACTIVITY SURVEY FORMAT (ALL 21 ITEMS)

Table 4

JENKINS ACTIVITY SURVEY FORM T (ALL 21 ITEMS)

RAW SCORES CONVERTED TO LOGS

287 MEASURABLE PERSONS WITH MEAN ABILITY = -0.52 and STD. DEV. = 0. 70

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item characteristic curves gained by subdividing the sample into 6 subgroups ranging from low to high ability is displayed in Table 5. The first group, that group with the lowest amount of Pattern A behavior scored within the 1-4 point range and contained 36 persons, while the 6th group, that group possessing the highest amount of Pattern A behavior, scored within the 14-20 point range and consisted of 24 persons. Groups 2. 3, 4 and 5 displayed the following score ranges and numbers of subjects respectively: Group 2 (5-6; 55); Group 3 (7-8; 61); Group 4 (9-10; 57); and Group 5 (11-13; 54).

The analysis ot the fit of the 21 items on 287 measurable persons resulted in most items, (i.e. 18 of the 21 items) to be in accord with the Rasch Hodel. The fit statistics are depicted on Table 6. These items were represented by total fit tests close to one, or within the reported standard deviation of .70. Items 8 (DRIV), 9 (COMP), and 10 (COM2) were the 3 items demonstrating a greater than one standard deviation from the model with total fit tests of -2.61 , -2.45 , and -2.27 respectively. Most of the 21 items demonstrated a left to right progression across the latent variable subgroups and did not depart significantly from the expected item characteristic curves, although some items did not differentiate as well between the designated subgroups. Table 7 represents the departure from the expected item characteristic curve. Referring again to Table 5 it can be seen that item 2 (STRE) did not demonstrate progression across the lower ability groups as is reflected in a similar proportion correct (.32, .. 33, .36) for the 3 lowest groups. There is for item 2 (STRE) a clearer progression noted between the third and fourth groups and

Table 5

ITEM CHARACTERISTiC CURVES

JENKINS ACTIVITY SURVEY FORM T (ALL 21 ITEHS)

ITEM FIT STATISTICS

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Table 7

 $\sigma_{\rm{max}}$ and $\sigma_{\rm{max}}$

DEPARTURE FROM EXPECTED ITEH CHARACTERISTIC CURVES

also between the fourth group and the fifth group. Yet, this item is represented by a similar proportion correct for fifth and sixth groups (.57, .58). The consequence of situation is seen in a fit between statistic of 2.59, a value greater than the total fit value. The total fit statistic for item 2 was 1.44, within a single standard deviation from one. In general, this item did not demonstrate a significant departure from model expectations, but failed to do well in discriminating between 6 ability subgroups. Rather than 6 ability subgroups, item 2 (STRE) reflects 3 subgroups and seems to do best in describing the movement from the lowest group to the middle group (subgroup 3) and from the middle group to subgroup 4 and subgroup 5. This discrimination index is .38 which reflects a lower than perfect capacity to differentiate between the 6 ability subgroups. With an N GROUP parameter, pre-designated ability groups had been of 3 rather than 6, the discrimination index would have been much closer to a value of one. This is not a bad item, but is one which does not work well in the 2 groups immediately below the middle group and in the highest group.

Item 3 (EAT1) reflects a situation similar to item 2 (STRE) while this item does not significantly depart from the model (total fit statistic is 1.46) the fit between statistic of 2.59 seemingly demonstrates a problem of left to right progression. Analysis of the item characteristic curve for item 3, labeled the EAT1, variable reveals that group 3 had a smaller proportion correct (.46) than group 2 (.55). In addition, the progression from group 4 (.54) to group 5 (.57) neglects to clearly differentiate between these 2

groups. The discrimination for this item (.47) although better than the item 2 value of .38 is still low. This item does not work well in the middle groups. In addition, the retrograde progression (group 3 to group 2) leads to the possibility of the presence of implausible response patterns.

The EAT2 variable, item 4, works well in both the lower subgroups and the higher groups. It does not do so for the middle groups. Note again the retrograde progression (group 4 down to group 2). The between groups fit statistic does not significantly depart from the model with a value of 1.48, but there still exists the possibility of improbable response patterns. Item variables LIST, WORD, and LATE (items 5, 6, 7) demonstrate fit and left to right progression with a discrimination index near one.

Items 8, 9, 10, and 11 (DRIV, COMP, COM2, and ACT1) all demonstrate progression across ability groups, yet the fit between statistics for these items are large (4.84; 4.55; 3.73; 2.03) signifying that these items are not fitting the Rasch Model expectations. Accompanying the high fit between statistics are discrimination indexes of 1.92, 1.83, 1.82 and 1.56 respectively, which give to these items an appearance of discriminating well between the 6 ability subgroups. Not only do these items seem to discriminate well but they seem to discriminate better than any of the remaining 17 item variables. In addition, the total fit statistics produced by these items are higher than those produced by any other item.

Further analysis was done to determine the possible meaning of the fit statistic and discrimination values of items 8, 9, 10, 11

(DRIV, COMP, COH2, ACTl). These unusually high indices led to further investigation of each of the 4 items: The item variables DRIV, COMP and *COM2* (items 8, 9 and 10) ask the respondent to rate himself in terms of hard driving competitive behavior. The respondent rates not only his own perception of his behavior (COHP, item 9), but also is asked to indicate his/her perceptions as to how others rate his/her behavior (DRIV, item 8 and COH2, item 9). The four response options available are identical for each item as is the placement of these options. The choices include: definitely hard driving and competitive; probably hard driving and competitive; probably more relaxed and easy going; and definitely more relaxed and easy going. A response set may have been created not only by the identical wording of the options but by the identical placement as well. Another issue which can be raised in reference to these items is related to the phenomenon of the perception of self and of self by others. Perception is a multi-variable psychological construct which may prove difficult to measure with a paper and pencil self-report instrument. Also to be considered is the fact that these 3 items, unlike the remaining JAS items, ask the individual to place himself or herself within a framework which is not explicitly defined. While hard driving competitive behavior is thought to be an essential component of Pattern A behavior, behavioral specifics are not present in the item variables (8, 9, 10) which attempt to measure it.

Item 11 (ACTl) is similar to items 8, 9, and 10 in that it asks the respondent to indicate how he or she perceives someone who knows him well would rate his/her general level of activity. While this

item variable did not significantly depart from the Rasch Model expectations with a total fit statistic within one standard deviation from a value of one, the fit between (2.03) and the discrimination index (1.55) were noticeably higher than most other items. Initial examination of the response choices demonstrates that the continuum of activity level is represented by the available choices of: too slow; about average; and too active. If a problem existed with the available choices, it may be related to the fact that the individual was given only 3 dimensions of activity level and was forced to choose one of them. For example, when considering the response alternative C which states: Too active; needs to slow down; in conjunction with response alternative A which states: Too slow; should be more active; an issue can be raised as to whether an individual can be either slow or active without being too slow. too active or just average as indicated by response alternative B.

Person characteristics may also be responsible for the misfit of items 8, 9, 10, 11, thus these items should not be viewed as misfitting in and of themselves until person fit has been analyzed. Irregular person records may result in contamination of results.

Item variable ENER (item 12) seemed to fit the model as did item variables TEMP (item 13) and TIME (item 14). The following 2 items: item 15 (TIM2) and item 16 (PROJ) did not significantly depart from the model but demonstrated some problem in their item characteristic curves. Both of these items demonstrated retrograde movement from subgroup 4 to subgroup 3, or a smaller logit proportion correct in subgroup 4 than in subgroup 3.

The item characteristic curve for the next item, item variable SCDL (item 17) was interesting as the lower subgroups (subgroups 1 and subgroups 2) did not score on this item and there was not a difference in the proportion of positively scored responses between subgroup 4 and subgroup 5. In addition, this item received a .25 value as its highest logit proportion correct. SCDL later proved to be the most intense item in the intensity ordering.

Item 18, item variable WORK, seemed less intense than any of the other 20 items. This item produced a value of .67 in the lowest latent variable group; a value of .85 for groups 2 and 3 and values ranging from .89 to .95 for subgroups 4-6; the highest logit proportion correct occurred in the 4th group. Later analysis demonstrated that this item was the least intense item in the intensity ordering provided by the model. The fit of this item was within acceptable model boundaries and the departure from the expected item characteristic curve was minute.

Item variables LEAD (item 19), RESP (item 20), and SERS (item 21) all produced discrimination indexes of 1.17, a value close to the desirable value of one. These items worked as the model would have it with those in the lower latent trait groups receiving a lower logit proportion correct than those in the higher latent variable groups. The fit statistics, both between fit and total fit resulted in values within a standard deviation of one. As stated previously, when items fit the model. the weighted mean square should not be too much different from the total fit value. Differences between these values for these items were within a standard deviation of each other.

Summary Rasch Fit Analysis. In summary, the fit of the 21 items contained on the Student Version of the Jenkins Activity resulted in total fit statistics within a standard deviation of a perfect fit value of one for 18 of the 21 items. The items not reflecting this criteria were items numbered 8, 9, and 10 (item variables DRIV, COMP, COl12). In addition, items 8, 9, 10 resulted in large fit between statistics as well as weighted mean square quite different in value from the total fit tests. The discrimination indexes resulting from the calibration of these items were the highest discrimination values obtained and upon initial inspection give the appearance of discriminating well between the pre-designated latent variable subgroups. Yet when the fit between statistics for items 8, 9, 10 were considered it was apparent that the misfit between groups was large.

Another item variable which did not function as well as others was ACT1 (item 11) resulted in a total fit value of 1.59 which while not as high as those values gained by items 8, 9, 10 was higher than all other remaining values. The weighted mean square value was .55, greater than a standard deviation from the total fit value. Another consideration important to item 11 (ACT1) was the fit between statistical value. This value of 2.03 was not as high as values produced by items other than 8, 9, and 10 and was considered in conjunction with a discrimination index of 1.55. Not a single person in the lowest latent variable group answered this item with a positive response. The Rasch Model assumes that at least some persons at the lower end of the latent variable being considered will answer the item with a positively scored response. Thus, item 11 (ACTl) does not hold entirely to this assumption.

Rasch Intensity Ordering

The second research question addressed in this study was as follows: If the 21 dichotomously scored items contained on the Student Version of the Jenkins Activity Survey fit the Rasch Latent Trait Model, can they be ordered in terms of intensity? For purposes of this study, the term intensity was defined as the difficulty parameter of the model. When persons manifest less of the latent variable than that required by the item, the probability of a positive response will be low.

The BICAL 3 computer output yielded 3 panels of ordering information which included: Serial Order, Difficulty (intensity). and Fit Order. This information is presented in Table 8, Table 9, and Table 10 respectively. Serial order output incorporated the following information: the item sequence number; the item name, the item difficulty (which as stated previously, was defined for study purposes as item intensity); the standard error of the item difficulty (See Appendix for mathematical formula); the items discrimination index and the total fit statistic for each item. The difficulty ordering output contains the same information as the serial order output with the only exception being that the items are listed in order of intensity (difficulty) ranging from the least intense item to the most intense item. The fit order output orders the item according to the fit statistical value, from worst to best fit, and gives in addition to the information provided

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ITEM INTENSITY ORDER

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by the intensity (difficulty) ordering,the fit between statistic, the weighted mean square and the point biserial correlation coefficient.

The calibration of these 21 Jenkins items on the total sample of 287 persons resulted in a mean item intensity (difficulty) of 0.00 with a standard deviation of 1.15. The least intense item was item 18 (item variable WORK) which gained an item intensity of -2.53. Asked of the person by this item was the question: How often do you bring work home with you? The question itself seemed straightforward and when viewed intuitively seemed to attempt to gain information regarding the presence of the latent variable being considered, namely Pattern A behavior. Hard driving competitive behavior, a major component of Pattern A behavior, would seem to be related to the frequency of bringing work home to be accomplished during what would be considered by others to be leisure time. Further examination of this item revealed that the 3 alternatives offered were: Rarely or never; once a week or less often; and more than once a week. These available alternatives may have been the reason this item was calibrated as the least intense item as none of the 3 choices seemed any more hard driving than typical student behavior.

The most intense item was item 17 (item variable SCDL) which received a value of +2.59. Thus, the range of item intensity was from -2.53 to +2.59. This SCDL item variable asked the question concerning the maintenance of a regular study schedule during vacation periods. Behavior such as this, studying when it is not necessary to do so, even intuitively seems to reflect the behavior of someone who is constantly outwardly striving to achieve. SCDL, the most intense

measure of Pattern A behavior, was followed by item variable LATE (item 7) which asks: How often do you arrive late when you tell someone you will meet them? The Pattern A response is alternative C which reads: "I am never late", which is a statement that is quite definitive of Pattern A behavior reflecting components of the operational definition of this behavior. The item intensity of the variable LATE (item 7) was 1.58 and was approximately an item standard deviation from item variable SCDL (item 17). SCDL and LATE thus calibrated a standard deviation apart. The standard error of measure associated with SCDL was .52, thus being 2 SEH away from LATE. The SEH associated with LATE was .31. These 2 items produced error values that were larger than values for any of the remaining 19 items. The remaining items calibrated with standard errors of measure ranging from .22 to .27.

Item variable WORD (item 6) followed by item variable EAT2 (item 4) displayed intensity values of 1.15 and 1.00 respectively. These 2 items were closer to each other than SCDL and LATE, being .15 logits apart. Item variable WORD (item 6) was .43 logits less than item variable LATE. The spread of these 4 items while seemingly inconsistent, should be viewed with reference to both their intensity values and the error of measure associated with them. Stated previously and depicted below on Table 11 are the item intensity values and the standard error of measurement associated with these 4 intense item variables (SCDL, LATE, WORD, EAT2; items 17, 7, 6, 4). Note that item 17 is almost 2 of its SEM of .52 from 7; that item 7 is approximately $1\frac{1}{2}$ of its SEM from item 6; and that item 6 is 1 SEM from item 4.

Viewed within the standard error framework assists placement of

Table 11

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THE FOUR HOST INTENSE ITEMS WITH ASSOCIATED ERROR

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these items in a linear dimension.

Item variables TIME, SERS, RESP, PROJ, LEAD and ACT! (Items numbered 14 , 21 , 20 , 16 , 19 , and $11)$ followed item variable EAT2 (item 4) in intensity. The intensity values for these items ranged from .80 to .20 and calibrated with the following values: TIME .80; SERS . 78; RESP .64; PROJ .37; LEAD .20 and ACTl .20. Table 12 depicts these item variables focusing on both item intensity and the error of measurement associated with each item. Item variables TIME and SERS were .02 logits apart and were less than a standard error of each other while moving down in item intensity from SERS to LEAD demonstrated a standard error of measure between each of these items. ACTl and LEAD calibrated at the same intensity level and manifested similar standard errors. The questions posed by these items are not similar as the ACTl item variable asks: How could your spouse or best friend rate your general level of activity? While item variable LEAD asks: When you are in a group, do the other people tend to look to you for leadership? These 2 items while apparently reflecting dissimilar behaviors were equally intense. Thus, it may be said that these items (ACT1 and LEAD) measure Pattern A behavior at the same intensity level, occupying the very same position on the linear dimension.

The remaining 11 items ranged in intensity from $-.04$ to -2.53 . All of these remaining 11 items calibrated below the mean intensity value of 0.00, and may be said to be items which measure the less intense aspects of Pattern A behavior. Table 13 depicts these items giving their item number, variable name, intensity value and the

 $\label{eq:2.1} \left\langle \left\langle \hat{\theta} \right\rangle \right\rangle = \left\langle \left\langle \hat{\theta} \right\rangle \right\rangle \left\langle \left\langle \hat{\theta} \right\rangle \right\rangle$

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INTENSITY OF ITEMS FOLLOWING EAT2

 $\label{eq:2} \mathcal{F}_{\text{max}}(\mathcal{A}) = \mathcal{F}_{\text{max}}(\mathcal{A})$

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ITEMS BELOW MEAN INTENSITY

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standard error of measurement associated with each. It is of interest to note that the standard error of measure was the same for 9 of these items differing only for the 2 least intense items (LIFE, WORK). Item variable ENER was a standard error of measure from LIST, but LIST and STRE seemed to occupy the same relative position. Item variable DRIV was considerably less intense than STRE, occupying a position approximately $3\frac{1}{2}$ standard errors below the STRE item variable. The intensity ordering from DRIV down to TIM2 demonstrated these values: +-.60 $(DRIV)$; $-.68$ (EAT1); and $-.71$ (TIM2). Again there was less than a standard error between these items giving them an almost identical linear position. Yet TIM2 was about a 1.5 standard errors from the next item variable TEMP. These 2 items do not occupy the same position. COHP and COM2, while less intense than TIM2, calibrated with intensity values which were similar. The progression from COM2 down to the least intense item on the Jenkins Activity Survey demonstrated that COM2 was 4 standard errors of measure more intense than the next item variable LIFE and that LIFE was 7.5 standard errors from the least intense item WORK. It was evident that the spread of items at the lower end of the Pattern A variable, namely those items below the mean intensity value of 0.00 demonstrated some item overlap in addition to wide gaps between items at the lower end of the variable.

Summary Rasch intensity ordering. The intensity ordering of the 21 Jenkins items resulted in the item variable WORK (item 18) as being the least intense item and item variable SCDL (item 17) as being the most intense item. The range

provided by the item calibration was -2.53 to $+2.59$ logits. Some of the items calibrated at intensity levels which were similar, so similar that they seemingly occupied the same position on a linear continuum. This was especially true for the items at the middle of the Pattern A variable continuum. The items at both extreme ends of the continuum were one logit apart from the next item respectively. Thus the items tended to overlap in the middle of the variable, leaving a wide gap at each extreme.

Guttman Scale Application

Analysis of the Guttman Scale computer output for the 10 most intense items defined by the Rasch Model analysis for the entire sample of subjects was considered prior to comparison with the Rasch ordering. These item variables included: ACT1, LEAD, PROJ, RESP, SERS, TIME, EAT2, WORD, LATE, and SCDL. The Guttman Scale ordering of these item variables was as is depicted in Table 14. The ordering being from the most intense to the least intense item, SCDL (item 17) would result in positive responses to the remaining 9 items. A score of 9 signifies that a positive response to the next most intense item LATE (item 7) would result in a positive response to the remaining 8 items. The same pattern is followed for the remaining items. This pattern is in accordance with the triangular response pattern which demonstrates the defined cumulative property of a Guttman Scale. Because a Guttman Scale represents a deterministic model each deviation from the expected triangular pattern is termed an error. Table 15 depicts the error associated with each item variable. The error

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GUTTMAN SCALE

ERROR

is classified in two ways designated by either "FAILING" or "PASSING". Note that FAILING signifies that individuals failed an item (did not answer the item with a positively scored TYPE A response) which should have been passed (answered with a positively scored TYPE A response). Conversely, PASSING signifies that an item was passed (that is answered with a positively scored TYPE A response) which should have been failed (answered with a negatively scored response). These operational definitions of PASSING and FAILING are the substance of the Guttman Scaling Model which states that a positive response to the most intense scaled item should result in a positive response to the remaining items of lesser intensity.

Table 16 illustrates the percentage distribution of positively scored responses. The most intense item in the Guttman analysis was answered with a positively scored response by only 5% of the subjects. This item was the item variable known as SCDL. ACTl and LEAD were the least intense items and were both answered with a positive response by 35% of the subjects. Because the number of subjects in the sample was 287 an increased percentage point reflects approximately 3 additional positive responses, more specifically 2.87 positive responses. Thus the percentage distribution of items reveals that 24 more subjects answered positively to the item variable LATE than did to the SCDL variable as well as the fact that the item variable SERS received only 3 more positively scored responses than did TIME the item variable preceding it. Another interesting manifestation of the Guttman percentage distribution is that these 10 item variables were answered with a positively scored response by no greater than 35% of the 287 subjects

Table _16

GUTTMAN SCALE

PERCENTAGE DISTRIBUTION OF POSITIVELY SCORED RESPONSES (N=287)

participating in the analysis.

The Coefficient of Reproducibility; the Minimum Marginal Reproducibility; the Percent Improvement and the Coefficient of Scalability derived from these item variables all received values less than values defined by Guttman Analysis to be acceptable. These values are presented in Table 17. The Coefficient of Reproducibility is .1381 less than the acceptable value of .9 which is said to reflect the extent to which a subject scale score is predictive of his/her response pattern. The Percent Improvement gained by subtracting the Coefficient of Reproducibility from the Minimum Marginal Reproducibility rendered a value of .0087 demonstrating the minute extent to which the reproducibility coefficient is due to just response patterns. The extremely low value (.0377) found for the coefficient of scalability is much below the desirable Guttman value of .6 or above. As stated previously scalability gives evidence of undimensionability and of the cumulative properties of a Guttman Scale.

Table 18 provides information regarding the interrelationships of items. The Yule's Q coefficient gives an item by item relationship, providing more specific information than the Biserial coefficient which relates a specific item to all other remaining items. It was interesting to note that ACTl, the least intense variable, demonstrated a relationship of greater than .4 with LEAD, RESP, SERS and EAT2 and gained a Biserial coefficient of .3983 while SCDL, the most intense variable demonstrated a relationship of greater than .4 with LEAD, PROJ, RESP and SERS with a Biserial coefficient of .3789. The variable with the highest Biserial coefficient was RESP (.4593) while

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GUTTNAN SCALE STATISTICS

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GUTTHAN SCALE COEFFICIENTS

the TIME variable displayed the smallest Biserial coefficient (.0262) indicating that the TIME item was not related to other items to any great extent.

Summary Guttman scale application. The 10 most intense items as defined by the Rasch Model calibration were subjected to an application of a Guttman Scale procedure. The resulting Guttman statistics were a coefficient of reproducibility of .7619 and a value of .0377 for a coefficient of scalability. These values were below the traditionally accepted Guttman values and were a reflection of the less than perfect response patterns found in the data. This analysis also presented item correlations. The item variable which correlated the highest with the remaining 9 items was RESP (.4593) while the item variable TIME demonstrated the smallest correlation. Both RESP and TIME were not in extreme positions in the intensity ordering.

Comparison of Rasch Intensity Ordering With Guttman Scale Ordering

The third research question was: How will the ordering of items accomplished with the Rasch Model compare to the item ordering of a Guttman Scaling procedure? When comparing the results of the Guttman Scaling procedure with the results from the Rasch calibration, many similarities and many differences were found. Table 19 compares the intensity ordering of the Guttman procedure to that of the Rasch calibration. As stated the 10 most intense items defined in the Rasch calibration were processed utilizing the Guttman Scaling

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COMPARISON OF RASCH AND GUTTMAN ORDERING

procedure. As expected, the intensity ordering of the 10 items was similar with both procedures. A difference in order did occur with the 2 least intense items. Both the Rasch calibration and the Guttman Scaling procedure evaluate an item's intensity by considering the number of positive responses to an item, thus both employ response methodology. The concern of each model being whether a subject selects the particular response which best indicates the relationship of the stimulus to the subject himself. Both models analyze each item by focusing upon the number of positively scored responses to the item and consequently comparing the items accordingly. The primary question addressed by each model is: Can the variable be represented by an ordinal scale?

In addition both models assume that the variable of interest is unidimensional and is represented by dichotomously scored items which are related to it. The Guttman Scaling Model is stated in terms of the ideal case and assumes responses to items to be determined by those parameters associated with subjects and items. Because of this "ideal case" within the Guttman Scaling Hodel statement, there is not a provision for error. Thus, the error associated with the Type AJ scale consisting of the 10 most intense item variables defined by the Rasch Model Calibration is seemingly large and does not fit the ideal cumulative Guttman Scale. Although the items did order in intensity in the same manner, with both the Guttman and Rasch analysis, the Guttman Scale application reflects considerable error. For example when considering the error associated with each item variable contained on Table 20 it is apparent that within the failed category, specifically

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PERCENTAGE OF GUTTMAN SCALE ERROR

those individuals who failed an item which should have been passed, the ACT1 and LEAD item variables were represented by one third and onehalf of the 287 subjects. It is also of interest to note that as the items move from greater to lesser intensity the percentage of error within the failed category progressively increases. The same phenomenon does not exist for the passed category. The percentage error associated with each item variable progressively increases as movement occurs from the most intense item (SCDL) to the item ranked fifth in intensity (TIME). From TIME down to LEAD, the least intense item, the percentage of error progressively decreases. Thus for the passed category most of the error is contained within the variables ranked in the middle.

Comparing the error resulting from the Guttman analysis to that of the Rasch fit analysis brought forth many interesting issues. The provision for error contained within the Rasch Model is a function of this model's probabilistic nature. The Rasch fit statistic allows for a mathematical decision concerning whether the obtained item intensity differs significantly from what theoretically would be expected by just chance alone. Table 21 presents the ranking of the 10 intense items decided by both the Guttman and the Rasch Models, the total Guttman error derived by adding the number of errors in both the passing and failing categories for each item; and the Rasch fit statistic. Note that most of the Rasch fit statistics do not deviate significantly greater than one standard deviation value (.70) away from a value of one. The only item variable which does so is ACTI with a fit statistic of -1.59.

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GUTTMAN ERROR AND RASCH FIT

Comparison of Rasch Intensity Order with Guttman Order. The ordering of items provided by both the Rasch Model and the Guttman Scaling Model was identical. The Rasch Model application resulted in nine of the ten items considered to statistically fit the model while the Guttman Scale application demonstrated considerable response error.

CHAPTER V

DISCUSSION

The application of the Rasch Model and Guttman Model to the same data produced similar results. Yet the Guttman Scaling Model does not fit the data while the data is demonstrated to fit the Rasch Model. Both of these models analyze items by considering the number of positive responses. The question then becomes why did the outcome of the Rasch Model application demonstrate the sought after fit while application of the Guttman Scaling Model result in a considerable amount of error? The complete determinism of the Guttman Model does not allow for deviation from the previously discussed triangular response pattern. This is a rigid expectation which allows for scaling of only those items which can adhere to this stringent model. Nothing can be accounted for by random variation. The model blatantly fits the items or it does not. Conversely, the Rasch One Parameter Latent Trait Hodel is nondeterministic allowing for variation which may be attributable to chance. The probabilistic character of the Rasch allows for the assumption that all elementary outcomes are equally likely. Thus the probability of a positively scored response to an item on the Student Version of the Jenkins Activity Survey is as equally likely as a response scored with a zero. The most elementary definition of probability stated in terms of a dichotomy is:

> (1) $\frac{P(A)}{P(A)} = .5$ $\frac{2}{\pi}$ Total $\#$ of outcomes (2) $P(B) = .5$

 $\frac{1}{10}$ Total $\#$ of outcomes

or

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The above equations demonstrate that event A (a pattern A response) is independent from event B (a pattern B response). The probabilistic functions of the Rasch Model thus allows for variation in responses beyond that determined by subject and item parameters, for probability theory regards event A to be as likely event B as the number of observations increases. As a direct consequence of this equally likely notion, the Rasch Model as all other probabilistic models does allow for the presence of a certain amount of unsystematic variation or error. Thus in the presence of the variation in the responses of the 287 subjects to the Jenkins Activity Survey, the Rasch Fit Statistics viewed how the sample observation deviated from probability expectations. The fit statistics obtained for each of the 21 items on the JAS-SV allowed for some variation.

Table 22 depicts the intensity ordering defined by both models as well as the Rasch item intensity estimates. These Rasch intensity estimates ranged in value from 2.59 to .20. In order to define a variable in accordance with the Rasch Model Wright and Stone (1979) have stated that for two items to define a line between them the difference between the Rasch intensity estimates of the two items should be greater than one standard error. This holds true for the distance between any two items.

An issue explored was to determine if the distance between each intensity estimate was adequate to demonstrate a linear direction to the latent variable that the items contained on the Student Version of the Jenkins Activity Survey (JAS-SV) is stated to measure, namely TYPE A or Coronary Prone Behavior.

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INTENSITY ORDERING WITH ASSOCIATED

RASCH INTENSITY ESTIMATES AND STANDARD ERROR

Figure 2 JENKINS ACTIVITY SURVEY-STUDENT VERSION

RASCH INTENSITY CALIBRATION

Logit Intensity Scale

Figure 2 depicts the 10 most intense items and their position on a linear logit scale. The linear log transformation utilized to convert item intensity (difficulty) into logits is seen in the appendix. Items 11 (ACTl) and 19 (LEAD) calibrated with the same intensity while items 14 (TIME),21 (SERS) and 20 (RESP) calibrated less than a standard error apart. Item 6 (WORD) and item 4 (EAT2) are barely a standard error apart. For variables to define a line there should be greater than a standard error between them. Thus it seems that at least 4 items can be deleted which may be measuring Pattern A behavior with the same intensity. The decision as to which specific items to delete may be arbitrary, as the item calibration is so similar. The assumption of the Rasch Model is that items calibrated at the same position on the logit scale are measuring the variable at a similar level of intensity (difficulty). Logically speaking, the items which best represent a necessary component of the operational definition of Pattern A behavior, in addition to being well constructed psychometrically should be retained. Thus, the possibilities for a 6 item Guttman-type Scale are viewed as all of the possible linear combinations of those items which are greater than a standard error apart. The clustering of items at .20 logits of intensity (items 11 and 19) and at .14 and .15 logits of intensity (items 14, 21, and 20) all seem to be deriving different aspects of the Pattern A behavior measured by the Jenkins Activity Survey-Student Version. The same does not hold true for items 4 (EAT2) and 6 (WORD) calibrated at . 16 1ogits of intensity which ask the subject to rate himself in terms of behavior which can be termed impatient. The relative importance of a

particular item to a new Guttman like.scale must then as previously stated, be determined by an intuitive decision of an item's contribution to variable definition.

Another strikingly apparent issue is derived from the intensity ordering of these 10 items. The most intense item (SCDL, item 17) is many standard errors away from the next item (LATE: item 7). While a positive response to this item may indeed measure Pattern A behavior, what about the logit intensity gap between SCDL and LATE? Additional items should be constructed in accord with the operational definition of the Pattern A variable focusing on the more intense aspects of the variable. Suggestions for additional items are presented in Appendix I. These items can be administered with the previously calibrated items to determine if they can be placed at the intensity levels between SCDL (2.59 logits) and LATE (1.58 logits). In addition to accomplishing this objective another objective will be realized. This additional objective is the demonstration of calibration invariance. The Rasch Model assumes sample free measure. Thus previously calibrated items should calibrate at a similar intensity level. This will guarantee reliability of the placement of these items at their respective positions on the logit scale.

Thus far it has been demonstrated that the Rasch Model intensity calibration of 10 items from the Student Version of the Jenkins Activity Survey compares favorably with the item ordering provided by Guttman Scale Analysis. The Rasch Model was shown to provide an additional benefit of item fit analysis derived from the probabilistic nature of the Rasch Model. It is also important to note that in

addition to intensity ordering and fit analysis, the Rasch Model can provide interval level measurement once a calibrated item's position on the logit scale is determined. This fact gives increased support for the utility of the Rasch Model in creating a Guttman like scale. A long established criticism of the Guttman Scaling Model is that it provides only ordinal level measurement for which parametric statistics may not be applicnble. With the Rasch Model, it may be possible to build a Guttman Scale with interval measurement properties.

CHAPTER VI

SUMMARY AND CONCLUSIONS

The purpose of this study was to determine if the 21 items contained on the Student Version of the Jenkins Activity Survey, a measure of Pattern A (coronary prone behavior) behavior, could be calibrated and ordered employing the one parameter latent trait model known as the Rasch Model. This primary purpose was partitioned into three major areas of inquiry which included: determining the statistical fit of the Rasch Model to the Jenkins Survey; determining how calibrated items would order in intensity and a subsequent comparison of the results of the Rasch fit analysis and ordering to a Guttman Scaling Model. A sample of 300 university students consented to respond to the Student Version of the Jenkins Activity Survey. Thirteen of the 300 questionnaires were eliminated because of incomplete responses.

The initial research problem was to determine if the 21 Jenkins items fit the Rasch Model. It was found that 18 of the 21 items were in accord with the model. The three misfitting items were items 8, 9, and 10 which ask the respondent to rate himself in terms of harddriving competitive behavior. Examination of these items revealed that the four response options available for these three items were identical as were the kind of behavior these items were attempting to identify .. Item 11, although exhibiting an acceptable

total fit statistic demonstrated misfit between the latent variable subgroupings. This phenonomen also occurred with items 8, 9, and 19 which demonstrated statistical misfit.

The intensity ordering provided by the Rasch item calibration resulted in item 17, that item which asks about maintaining a regular study schedule over vacation periods as being the most intense measure of Pattern A Behavior, the latent variable under consideration. This item calibrated at 2.59 on the linear log scale of the Rasch Model. The ten most intense items were as follows: item 17 (SCDL); item 7 (LATE); item 6 (WORD); item 4 (EAT2); item 14 (TIME); item 21 (SERS); item 20 (RESP); item 16 (PROJ); item 19 (LEAD) and item 11 (ACTI).

These ten items were then subjected to the Guttman Scaling Model in order to compare the Guttman approach to the Rasch approach. It was found that the ordering of these ten items was identical for both models. The Guttman analysis demonstrated unacceptable reproducibility and scalability values, as well as considerable response error. Yet, the Rasch analysis demonstrated acceptable total fit statistics for each of the ten items. The only misfit occurring with these items was the fit between statistic found in item 11 which was coupled with a discrimination index of greater than one. This item did not function as the model would predict. What occurred was that too many individuals who answered positively to more intense items answered negatively to this item. Comparing the Rasch and Guttman outcomes clearly demonstrates the utility of the Rasch probabilistic approach which allows for the existence of a degree of error. It is reasonable to assume that items which are to measure a variable will never be totally

infallible. The Rasch Model, unlike the Guttman Model allows for a degree of error to exist and is not bound by absolute determinism.

It was also demonstrated that the Jenkins Activity Survey-Student Version can be improved as a consequence of this Rasch Model application. For example, the most intense items can be retained while the least intense items may be discarded as it can be assumed that almost everyone will answer a low intensity item with a positively scored response. Other items which may be deleted are those items demonstrating model misfit. Additional items should be constructed and calibrated to measure the more intense manifestations of the variable. This will assist to fill the gap between the most intense item, item 17 (SCDL) and the item which follows it, item 7 (LATE).

It can be concluded that the Rasch Latent Trait Model may provide a more reasonable approach to creating a Guttman Scale. The Rasch Model, in addition to providing an intensity ordering of items will also assist to create an interval measure. Items calibrated on the linear-log scale (logit) by the Rasch Model can be placed at specified intervals on a line. Those items demonstrating than a standard error between them define a position in the assumed unidimensional latent space occupied by the variable under consideration.

The major criticism of the Guttman Scaling Model is that criticism given to deterministic models, namely that these models lack statistical tests of item fit. In addition, the Guttman Scaling Model provides only an ordinal level measure. These criticisms seem to be answered by the Rasch Model, as the outcomes provided here

suggest that the Rasch not only may be used to create a Guttman Scale, but that this Guttman Scale can exhibit interval level measurement. This is a new and relatively unexplored application of this one parameter latent trait model. Although an existing measure of an operationally defined variable was used to describe this process, an approach such as this need not be limited to existing behavioral instruments. New measures can be constructed in this way, once the latent variable is defined and items are constructed to measure the variable.

A Rasch Model approach to a Guttman Scale, possessing interval level measurement properties would certainly assist to improve measures of behavioral phenomenon. The number of items needed to measure a behavioral variable could be reduced. In addition, a positive response to an item calibrated at the intense level of a variable would give information concerning a subject's response to less intense items, locate the amount of the variable exhibited by the subject on a linear logit scale, and provide an interval measure of the variable. Each of the above factors are desirable properties of objective measurement. Variables will as a consequence have meaning. The relationship between each item and the variable will be known. This will allow inferences to be made concerning the amount of the variable possessed by each subject.

Several implications exist as a consequence of this study. These implications not only serve Educational Research and Measurement, but all disciplines engaged in the measurement of behavioral variables. Current applications of the Rasch Latent Trait Model are seen in the realm of achievement testing and include item banking, test development, as well as tailored testing. These may also be applied to behavioral measures as well. What has been demonstrated in this study has been yet another application of this model. For the educator as well as the clinician, objective measurement of student's attitudes and behaviors may provide necessary information. For example, knowledge concerning variables such as anxiety and stress in the university student has always been limited by the instruments used to measure them. This has been the case of Pattern A Behavior measured by the Student Version of the Jenkins Activity Survey. Working to make the Jenkins Survey an objective, specifically an interval Guttman Scale would assist to identify those college students who possess a high degree of this behavior by asking just a few questions. An approach such as this would be an effective screening device to be used in the prevention of coronary heart disease, a ' major American health problem.

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APPENDIX A

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APPENDIX A

RASCH MODEL

Notion of objective methods for transforming observation into measurement.

Analogy: Measuring height for when someone says they are 5'6" tall, we do not ask to see the yardstick and we also know that another person who is 5'6" tall will measure the same even if a different yardstick is used.

OBJECTIVE HEASUREMENT:

BASIS:

- Λ. 1. Calibration of measuring instruments must be independent of those objects used for calibration.
	- 2. Measurement of objects must be independent of the instrument used for calibration.

STATEMENT OF RASCH MODEL:

When any individual encounters any item, the outcome is determined by the product of that individual's ability and the easiness of the item.

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APPENDIX B

APPENDIX B

RASCH MODEL

ANALYSIS OF FIT

- I. Purpose: The purpose of analyzing the manner in which the data fit the Rasch Model is to examine the plausibility of responses.
- II. Procedure: Standardized residuals are utilized to determine significant deviations from model expectations.
- Ill. The sequence of steps necessary to determine the fit of data to the Rasch Model is as follows:
	- A. Observe the difference between the estimates of difficulty for each subject and each item $(b_v - d_i)$
		- 1. The greater the positive difference, the easier the item.
		- 2. When the difference becomes more negative, the item becomes increasingly difficult.
	- B. The equation for the estimated P_{V1} for response X_{V1} is:

 P_{V1} = exp(b_v-d_i)/1 + exp (b_v-d_i)

- 1. b_v = estimated ability of person v.
- 2. d_i = estimated difficulty calibration of item i.
- 3. P_{vi} = (an estimated probability) will be used as the expected value of response Xvi.
- C. The expected variance of response X_{vi} is:

 $P_{\rm vt}(1 - P_{\rm vt})$

D. The standardized residual for X_{vi} given P_{vi} is:

$$
Z_{\mathbf{vi}} = (X_{\mathbf{vi}} - P_{\mathbf{vi}})/\sqrt{P_{\mathbf{vi}}}(1 - P_{\mathbf{vi}})/\vec{r}^{2}
$$

Thus the expected value P_{vi} for each observation subtracted from the observation in question (xvi). The residual difference is standardized by the scaling divisor $\sqrt{p}_{\text{vi}}(1 - P_{\text{vi}})\overline{l}^2$. Following this procedure gives all residuals a mean of $\overline{0}$ and a standard deviation of 1. Note that the scaling divisor is

the binomial standard deviation of the observation. If the data fit the Rasch Model the outcome will be that the standardized residual Zvi will be distributed as a normal dis-Thus the mean will be approximately 0 and the standard deviation will be approximately 1.

The squares of the standardized residuals will be distributed according to the chi square distribution.

- E. Specific to the dichotomous response situation (scored with either a "1" or a "0" are the following equations:
	- 1. When $x = 0$:
		- a. $Z_0 = -e^{(\sqrt{b} d)/27}$ b. $Z_0^2 = \exp(b - d)$
	- 2. When $x = 1$:
		- a. $Z_1 = \pm \exp{\sqrt{d} b}/\sqrt{27}$ B. $Z_{1}^{2} = \exp(d - b)$.
- F. To evaluate the fit of each item and each subject the following steps will be taken:
	- 1. To determine item fit the item's vector of standard square residuals (Z^2 vi) over the sample of $v = 1$, N subjects are summed. The misfit statistic for items given by the following equation is calculated

$$
Vi = \frac{N}{V} Z^2 vi / (N - 1) \qquad F_N - 1, \sim
$$

2. To determine the fit of each subject v, the subjects vector of standard square residuals (Z vi) over the test of $i = 1$, L items are summed. The misfit statistic is calculated.

$$
Vv = \frac{L}{1} Z^2 vi / (L - 1) \qquad F_L - 1, \sim
$$

APPENDIX C

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APPENDIX C

RASCH ITEM CALIBRATION

I. Preliminary Steps

- A. Construct a subject by item matrix. For dichotomously scored items, a 1 designates a positive response and \overline{a} 0 a negative response.
- B. This phase involves editing the subject by item matrix. Subjects and items which cannot be calibrated are removed. The criteria for removal of subjects are those with **all** correct or incorrect responses. The same is true for
items. Those items with all correct or incorrect rest Those items with all correct or incorrect responses are removed.
- C. Next the distributions of person scores and item scores are constructed. The scores are given as a proportion of a maximum possible value in combination with the frequency of occurrence of each proportion.

The proportions are converted to log odds or logits. The conversion to logits is accomplished in the following way:

- 1) For items: the natural log of the proportion incorrect is divided by the proportion correct.
- 2) For subjects: the natural log of the proportion of successes is divided by failures.

The converted proportions are bound by 0 and 1 and form a new scale which extends from $-\infty$ to $+\infty$. The new scale is linear in terms of the underlying variable. The variable will increase with the proportion of incorrect responses when item difficulty is considered. The variable will also increase with the proportion of correct responses.

D. The mean and variance for each logit distribution is computed (The subject logit distribution and the item logit distribution)

II. Obtaining Initial Item Calibrations

- A. Construct a grouped distribution consisting of nine columns. These nine columns can be viewed as the sequence of steps taken to obtain the initial calibration of items.
- B. The column headings (or sequence) includes the following:
- 1) Column 1 is the item label (the number of the item)
- 2) Column 2 is the item score (the number of positive responses to the item e.g. those items scored 1.)
- 3) Column 3 is the item frequence. (The frequency of items at each score group).
- 4) Column 4 is item scores converted into proportion correct. (Proportion i = Si/N)
- 5) Column 5 converts proportion correct into proportion incorrect. $(1 - Pi)$
- 6) Column 6 converts this proportion into logits incorrect. Note that to obtain each item score group logit the proportion correct and proportion incorrect is obtained. Then the natural log for each is determined. $(xi = ln/(1 - pi)/pi/$
- 7) Column 7 is the product of the item frequency and the logit incorrect. (fiXi)
- 8) Column 8 is the product of the item frequency and logit incorrect squared.
	- a) Mean for item logits: $X = \frac{G}{1} f i X i / L$
	- b) Variance for item logits: $U = (\frac{G}{4} f 1 X i^2) - (Lx^2.)/L$
- 9) Column 9 contains the initial item calibrations designated by d i. $(d i = Xi - x.)$
- III. Obtaining Initial Subject Calibrations
	- A. Construct a grouped distribution of columns which can be viewed as the sequence of steps necessary to obtain initial subject calibrations.
	- B. The column headings (or sequence of steps) include:
		- 1) Column 1 is each possible person score.
		- 2) Column 2 is the frequency of individuals at each score. (Note $N = total$ number of subjects)
		- 3) Column 3 is the proportion correct. $(Pr=r/L)$

4) Column 4 obtains the logit correct for subjects.

 $(Yr = ln/\overline{P}r/1 - Pr7)$

- 5) Column 5 gives the product of the subject frequency and logit correct.
- 6) Column 6 gives the product of subject frequency and logit correct squared. (NrYr)
- 7) Column 7 gives the correction for test width (br =yr); note it is the same as logit correct for subjects as the score logits, are already centered by the symmetry of the distribution of possible scores.
- 8) The mean and variance for subject logits are calculated.
	- a) Mean for subject logits: $V = \frac{L-1}{r} n r Y r / N$
	- b) Variance for subject logits: $V = \frac{L-1}{r}$ nr (Yr - Y.)²/N - 1
- IV. Expansion Factor Calculation
	- A. Purpose
		- 1) To correct the item calibrations for sample spread.
		- 2) To correct subject measures for test width.
	- B. Subject Expansion:

$$
X = \frac{1 + U/2.89}{1 - UV/8.35}
$$

C. Item Expansion:

$$
X = \frac{1 + V/2.89}{1 - UV/8.35}
$$
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- V. Corrected Calibrations
	- A. Corrected item calibrations:
		- 1) di = Ydi (this is the initial calibration multiplied by the expansion factor)
		- 2) Standard error of corrected item calibrations:

 $SE(di) = Y/\overline{N}/s1(N - Si)/i_2$

B. Corrected subject calibrations:

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 $SE(br) = x/L/r(L - r)/l_2$

VI. The Notation Used is as Follows:

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APPENDIX D

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APPENDIX D

JENKINS ACTIVITY SURVEY

FORM T

The instrument utilized in this study was the Jenkins Activity Survey, Form T which is the Student Version. The first twenty one items are those items which comprise the entire original instrument. The responses which are preceded by an asterik are those responses which were scored with a one and are indicative of a Pattern A response. Items twenty-two through twenty-eight were added to secure demographic data for the present study.

APPENDIX D

THE JENKINS ACTIVITY SURVEY Form T

Health care research is trying to track down the causes of several diseases which are attacking increasing numbers of people. This survey is part of such a research effort.

Please answer the questions on the following pages by marking the answers that are true <u>for you</u>. Each person is different, so there are no "right" or "wrong" answers. Of course, all you tell us is strictly confidential--to be seen only by the research team. Do not ask anyone else about how to reply to the items. It is your personal opinion that we want.

Your assistance will be greatly appreciated.

For each of the following items, please circle the number of the ONE best answer:

1. Is your everyday life filled mostly by

- *A. Problems needing solution Challenges needing to be met. C. A rather predictable routine of events.
	- D. Not enough things to keep me interested or busy.

2. When you are under pressure or stress, do you usually:

- *A. Do something about it immediately. Plan carefully before taking any action.
- 3. Ordinarily, how rapidly do you eat?
	- *A. I'm usually the first one finished. *B. I eat a little faster than average. C. I eat at about the same speed as most people. D. I eat more slowly than most people.

4. Has your spouse or some friend ever told you that you eat too fast?

*A. Yes often B. Yes, once or twice C. No, no one has told me this.

5. When you listen to someone talking, and this person takes too long to come to the point, do you feel like hurrying him along?

 A . Frequently B. Occasionally C. Almost never

6. How often do you actually "put words in his mouth" in order to speed things up?

*A. Frequently B. Occasionally C. Almost never

7. If you tell your spouse or a friend that you will meet them somewhere at a definite time, how often do you arrive late?

A. Once in a while B. Rarely *C. I am never late

- 8. Do most people consider you to be
	- *A. Definitely hard-driving and competitive?
	- Probably hard-driving and competitive?
	- C. Probably more relaxed and easy going?
	- D. Definitely more relaxed and easy going?
- 9. Nowadays, do you consider yourself to be?
	- *A. Definitely hard-driving and competitive?
	- Probably hard-driving and competitive?
	- C. Probably more relaxed and easy going?
	- D. Definitely relaxed and easy going?
- 10. How would your spouse (or closest friend) rate you?
	- *A. Definitely hard-driving and competitive?
	- Probably hard-driving and competitive?
	- C. Probably relaxed and easy going?
	- D. Definitely relaxed and easy going?
- 11. How would your spouse (or best friend) rate your general level of activity?
	- A. Too slow. Should be more active.
	- B. About average. Is busy much of the time.
	- *C. Too active. Needs to slow down.
- 12. Would people who know you well agree that you have less energy than most people?

13. How was your "temper" when you were younger?

14. How often are there deadlines in your courses? (If deadlines occur irregularly, please circle the closest answer below).

- 15. Do you ever set deadlines or quotas for yourself in courses or other things?
	- A. No B. Yes, but only occasionally
*C. Yes, once per week or more Yes, once per week or more often
- 16. In school do you ever keep two projects moving forward at the same time by shifting back and forth rapidly from one to the other?
	- A. No, never B. Yes, but only in emergencies *C. Yes, regularly
- 17. Do you maintain a regular study schedule during vacations such as Thanksgiving, Christmas, and Easter?

*A. Yes B. No C. Sometimes

- 18. How often do you bring your work home with you at night or study materials related to your. courses?
	- A. Rarely or never
	- B. Once a week or less often
*C. More than once a week
	- More than once a week
- 19. When you are in a group, do the other people tend to look to you to provide leadership?
	- A. Rarely.
	- B. About as often as they look to others.
	- *C. More often than they look to others.

IN EACH OF THE FOLLOWING QUESTIONS, PLEASE COMPARE YOURSELF WITH THE AVERAGE STUDENT AT YOUR UNIVERSITY. PLEASE CIRCLE THE MOST ACCURATE DESCRIPTION.

20. In sense of responsibility, I am

21. I approach life in general

Please answer the following general information questions.

22. Year of College Studies.

- A. First year
B. Second yea:
- B. Second year
C. Third year
- C. Third year
D. Fourth yea
- Fourth year
- E. Graduate Student

23. Sex

- A. Female
B. Male
- Male

24. Have you ever been told you have high blood pressure?

*A. Yes B. No

25. Do you smoke cigarettes?

*A. Yes B. No

26. Does anyone in your family, including yourself have diabetes?

- *A. Yes
- B. No
- 27. Which of the following would you consider yourself to be regarding your body weight?

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- *A. Overweight
- B. Underweight
- C. Average weight

28. Does anyone in your family have heart disease?

- *A. Yes
	- B. No

APPENDIX E

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APPENDIX E

JENKINS ACTIVITY SURVEY-STUDENT VERSION: ITEMS WITH ASSOCIATED* ITEM VARIABLE NAMES

 $\mathcal{F}^{\text{in}}_{\text{c}}(\mathbb{R}^n)$

 $\label{eq:2.1} \frac{1}{\sqrt{2\pi}}\int_{0}^{\infty}\frac{1}{\sqrt{2\pi}}\left(\frac{1}{\sqrt{2\pi}}\right)^{2\alpha}d\mu\,d\mu\,.$

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APPENDIX F

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APPENDIX F

BICAL (WRIGHT and MEAD, 1978) RASCH ITEM CALIBRATION

- Estimation Procedures: Prox and UCON (Wright and Panchapakesan, 1969; Wright and Douglas, 1975, 1977)
- Control Specifications:
	- NITEM (number of items)
	- NGROP (smallest subgroup size of at least 10 subjects; subgroups forms for purpose of analyzing fit of item data)
	- MINSC (minimum score is 1)
	- MAXSC (maximum score is dependent upon number of items)
	- LREC (record length)
	- KCAB (calibration procedure: $1 = PROX$ and $2 = UCON$
	- SCORE (control code for dichotomous $data = 0.$

Output Tables:

- Response Frequences for each Response Alternative
- Editing Process Table
- Sample Person (Subject) Ability Distribution
- Test Item Easiness Distribution
- Complete Score Equivalence Table
- Item Characteristic Curves and Fit Analysis
- Item Calibration summary giving: serial order, difficulty order, and fit order.

APPENDIX G

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APPENDIX G

Factor Analysis

Introduction

A factor analytic application was proposed as a research alternative. While it was not necessary to factor analyze the responses to the 21 item Student Version of the Jenkins Activity Survey, the procedure was performed to satisfy research curiosity. Of concern was the unidimensionality of the variable measured by the Jenkins, specifically Pattern A behavior. Unidimensionality would be demonstrated by the reduction of the 21 item variable to a single orthogonal factor.

Results Factor Analysis

The responses of all 287 persons to the 21 items on the Jenkins instrument were factor analyzed. A principle components analysis with a varimax rotation was the specific factor analytic approach employed. A factor loading of at least .5 was considered to be an acceptable value to include a variable in a factor definition (Gorsuch, 1977).

Table 23 depicts the 21 item variables and their respective communality estimates. The communality estimates provided the initial step in the attempt to find mathematical solutions which would specify factors entirely in terms of the common variance among variables. Communalities are numbers which appear in the diagonal of the correlation matrix which are generally less than one. It was interesting to note that item variables DRIV, COMP and COM2 (items 8, 9 and 10) received the highers communality estimates. ACTl, EATl, EAT2, TIM2,

Table 23

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COMMUNALITY ESTIMATES

PROJ, RESP and SERS followed with communality estimates ranging from .31836 down to .20467. These communality estimates were verified by viewing the correlation matrix and comparing the largest correlation in each row with the communality estimates provided by the computer output (SPSS, 1975).

On Table 24 is displayed eigenvalues and percent of variance accounted for by 21 factors in the unrotated matrix. The commonly employed criteria for delimiting factors was used. These criteria were specifically: a minimum of 5% of explained variance and an eigenvalue of greater than one. Factors 1 through 8 clearly met these criteria with Factor 1 displaying an eigenvalue of 3.28352 and Factor 8 displaying an eigenvalue of 1.02776. The percentage of variance accounted for by Factor 1 was 15.6% with Factor 8 accounting for 4.9% of the variance. The total variance accounted for by these 8 factors was 60. 1%.

The Varimax Rotated Factor Matrix is depicted in Table 25. Those item variables which received factor loadings of .5 or greater were considered. The .5 criteria was met by the following item variables within Factor 1: DRIV which loaded with a value of .64373, COMP with a loading of .69705 and COM2 with a .83192 loading. Thus, Factor 1 contains the hard driving and competitive components of the Pattern A (Coronary Prone) variable. Factor 2 was defined by the EAT item variables, e.g., EAT1 and EAT2 which loaded with values of .72286 and .61024 respectively. RESP and SERS were the variables meeting the .5 or greater criteria within Factor 3. Factor 4 was defined by the TIM2 variable while Factors 5 and 6 contained 2 item variables to be

Table 24

EIGENVALUES AND PERCENT OF VARIANCE UNROTATED MATRIX 21 ITEM JENKINS ACTIVITY SURVEY-SV

Table 25

VARIMAX ROTATED FACTOR MATRIX

included in their definitions. Factors 7 and 8 both contained a single variable loading at .5 or greater.

Summarization of the Varimax Rotation is contained in the following Table (Table 26). These findings were viewed in conjunction with the eigenvalues and percent variation resulting from the Varimax Rotation. Factors 1 and 2 both met the eigenvalue criteria of a value greater than one. These first two factors were the only factors meeting this criteria. Factor 1 defined by the DRIV and COMP variables accounted for 35.6% of the variance while Factor 2 defined by the 2 EAT variables explained 18.6% of the variance. Together these 2 factors explained over half of the variance (54.2%).

The above results were compared to the results obtained by Jenkins and Glass (1977). Jenkins found 3 orthogonal factors to be present in the factor analyses of the Adult Version of the Jenkins Activity Survey. He named these factors speed and impatience (S), hard driving and competitive (H), and job involvement (J). Glass found 2 orthogonal factors in the analyses of the Student Version of the JAS which he stated paralleled the S and H factors of the adult version. The present findings revealed both similarities and differences. First of all, Factor 1 was defined by the DRIV and COHP variables, thus, demonstrating congruence to the H factor of the previous analyses. Factor 2 defined by the 2 EAT variables can be said to be in part similar to the S factor defined by Jenkins and Glass. While the present analysis found greater than 50% of the variance accounted for by the first 2 factors, 6 additional orthogonal factors were identified signifying the possibility of the

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SUMMARY OF VARIMAX ROTATION

operational definition of Pattern A behavior in students being defined by 8 variables rather than only two. Three of the 8 factors were defined by only one significant variable loading, four of the 8 by 2 significant variable loadings with one factor (Factor 1) by significant loadings on 3 variables.

Linking the above findings to the findings provided by the Rasch fit analysis and item calibration revealed: 1) that the worst fitting item variables found on the Rasch fit analysis were those item variables having the highest loadings within Factor 1, that factor accounting for 35.6% of the variance. An explanation to be considered as a possible cause of this phenomenon is related to the fact that Rasch fit analysis, unlike factor analysis focuses on item responses. The Rasch misfit may, in part, be explained by invalid response patterns or to insufficient alternatives to these items making response difficult.

Another area which was interesting to explore was how the 8 orthogonal factors compared to the intensity ordering of the Rasch analysis. Table 27 depicts the 8 orthogonal factors, the variables which define each factor, and the ranking of these variables in intensity. Note that the intensity range is from 1-21 with a 1 representing the rank of least intensity and a 21 representing the most intense ranking.

Discussion Factor Analysis

The results of the factor analysis demonstrated the presence of 8 orthogonal factors which may imply that the variable under consideration is not of a single dimension or that the factor results are statistically artifact. In reference to the dimensionality issue it

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FACTOR LOADINGS AND RASCH INTENSITY

can be said that the operational definition of Pattern A behavior is represented by many facets which are evidenced in the eight orthogonal factors. To defend the unidimensionality of Pattern A behavior requires only to look to the operational definition of this variable. It should be remembered that Rosenman (1966) described Pattern A behavior in the following way:

"Pattern A appears to be a particular action emotion complex which is exhibited by an individual who is engaged in a relatively chronic and excessive struggle to obtain an obsessive number of things from his environment in too short a period of time, or against opposing efforts of other persons or things in the same environment." Thus, being overly competitive, ambitious, hard driving and time conscious are all typical Pattern A behaviors.

With the above definition in mind Pattern A behavior becomes the single latent variable under consideration. Wright and Stone (1979) state that the operational definition of the variable is an important step which must be taken prior to application of the Rasch Model.

Other explanations for the emergence of eight rather than one orthogonal factors may be related to the fact that latent trait models are nonlinear (the Rasch Model employs a linear log transformation) while factor analytic models are linear. As a consequence of this, the factors may reflect nonlinearity in data (Hambleton, 1978). Also if items measuring a variable are dependent, that is, if there is overlap between them, factor analysis may be misleading. Nunnally (1967) refers to *a* change in factor structure when overlapping items were removed from the M.M.P.I.

In addition, Torgerson (1958) discusses the fact that correlations between items in a perfect scale will always be represented by a response table with a zero cell. A perfect scale occurs when all individuals who respond with a positively scored response to an item of a given rank will also respond in the same way to items of a lesser rank. Thus, in a perfect scale the correlation between items is always unity. In situations in which all items are scored in the same direction, the matrix of interitem correlations will be a matrix of positive ones. Torgerson goes on to state that a factor analysis of such a matrix would yield a single factor. This single factor would possess items with loadings all equal to unity.

The above situation occurs when the correlation is between variables treated as dichotomous. When biserial correlations are considered (dichotomous with continuous variable) the result is not the same. Even though items form a perfect scale these correlations may range from zero to almost unity. Generally when items are ordered or ranked in terms of the specified underlying latent variable, any array of the interitem correlations will manifest itself by coefficient size decreasing on each side of the principal diagonal. Because the size of biserial correlations depend upon the marginal distribution of items, a factor analysis will yield as many factors as there are items. Unity can only be achieved when two items have identical marginals.

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APPENDIX H

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Psychiatry : of Behavioral Epidemiology

December 19, 1978

Karyn Holm, Assistant Professor Rush University, College of Nursing Schweppe Sprague Room 918 1743 W. Harrison Chicago, IL 60612

Dear Ms. Holm:

Thank you for your recent letter inquiring into the Jenkins Activity Survey and Form T, the student version by Dr. David Glass.

This form is very similar to Form B, that used for employed persons, but all reference to activities and job have been changed to make it more applicable to a student's life.

At the present time, the Jenkins Activity Survey has been placed in the hands of a reputable publisher, the Psychological Corporation, who will be providing forms, scoring services, and a manual to the general public shortly. At such time that this does become available on the market, we must request that you go directly through them. Dr. Glass will provide the test form and scoring key for you now.

Good luck with your work.

Sincerely yours, David Julius 743.

C. David Jenkins, Ph.D. Director Department of Behavioral Epidemiology

CDJ :BTH

The Graduate School and University Center

of the City University of New York Graduate Center: 33 West 42 Street. New York. N.Y. 10036

November 13, 1978

Professor Karyn Holm Rush University Schweppe Sprague #918 College of Nursing 1743 West Harrison Street Chicago, Illinois 60612

Dear Professor Holm:

Permission to use the Jenkins Activity Survey must be obtained from Dr. C. David Jenkins of Boston University Medical School. If he agrees, I will be happy to send you the student version of the JAS.

Sincerely, $\sum_{\text{Quadro. Glass}}$

Professor of Psychology

DCG:ai

APPENDIX I

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APPENDIX 1

SUGGESTIONS FOR NEW ITEMS

MODIFIED ACTIVITY SCALE

(from Jenkins Activity Survey)

- 1. Is your everyday life filled mostly by
	- A. Problems needing solution or challenges needing to be met.
	- B. Routine ups and downs.
	- C. Only occasional problems.
	- D. Not enough things to keep me busy.
- 2. Some people live a calm, predictable life. Others find themselves often facing unexpected changes, frequent interruptions, or "things going wrong". How often would you say you are faced with "things going wrong"? ·
	- A. Several times a day.
	- B. About once a day.
C. A few times a wee
	- A few times a week.
	- D. Once a week.
	- E. Once a month or less.
- 3. When under pressure or stress do you
	- A. Tend to act immediately.
	- B. Make careful plans to deal with it.
C. Struggle to keep up with your respo
	- C. Struggle to keep up with your responsibilities.
	- Share some of the burden with others who might prove helpful.
- 4. Ordinarily how rapidly do you eat?
	- A. I am always the first one finished.
B. I eat a little faster than most peo
	- B. I eat a little faster than most people.
C. I eat at about the same speed as most p
	- C. I eat at about the same speed as most people.
D. I eat more slowly than most people.
	- I eat more slowly than most people.
- 5. Has your spouse or a friend ever told you that you eat too fast?
	- A. No one has ever told me that I eat too fast.
	- B. I've been told this once or twice.
C. Occasionally I'm told I eat too fa
	- C. Occasionally I'm told I eat too fast.
D. People frequently tell me I eat too f
	- People frequently tell me I eat too fast.
- 6. Do you find yourself hurrying to get places even when there is plenty of time?
-
- A. Always C. Occasionally
- B. Often D. Never
- 7. If you tell your spouse or a friend that you will meet them somewhere at a definite time, how often do you arrive late?
	- A. Always C. Occasionally Rarely
- 8. When you are supposed to meet someone and they are already late will you
	- A. Sit and wait calmly?
	- B. Sit and wait but feel impatient?
C. Walk while waiting?
	- C. Walk while waiting?
D. Carry something to
	- Carry something to read or writing paper so that you can get something done while waiting?
- 9. When you listen to someone talking and this person takes too long to come to the point, do you feel like hurrying him along?
	- A. Always C. Occasionally B. Frequently D. Never
- 10. How often do you actually "put words in his mouth" in order to speed things up?
	- A. Never c. Frequently $Occasionally$ D.
- 11. How is your temper nowadays?

- 12. How often do you feel under pressure to produce in your courses?
	- A. Daily c. Once a week
B. Several times a week b. Every few we Several times a week D. Every few weeks
- 13. How often do you work overtime in your courses?

- 14. Do you work on two or more projects at the same time rapidly shifting back and forth from one to another?
	- A. All the time--it's the only way I can get things done B. Once in a while when it seems necessary
C. Only in emergencies--like at the end of Only in emergencies--like at the end of the grading period D. Never--it's not worth it
- 15. How would your spouse or a best friend rate your general level of activity?
	- A. Much too slow--just can't seem to get going
B. Slower than average--needs to be a little mo
	- B. Slower than average--needs to be a little more active
C. Average--busy much of the time
	- Average--busy much of the time
	- D. Too active--really needs to slow down
- 16. How do you think most people consider you
	- A. Always relaxed and easy going
	- B. Usually relaxed and easy going
C. Tend toward hard driving and co
	- Tend toward hard driving and competitive
	- D. Definitely hard driving and competitive
- 17. When in a group do other people tend to look to you to provide leadership?
	- A. All the time
	- B. More often than they look to others
C. About as often as they look to other
	- C. About as often as they look to others
D. Not as often as they look to others
	- Not as often as they look to others
- 18. Do you make yourself written lists of "Things to Do" to help you remember what needs to be done?

19. Would a spouse or close friend say that in your work you

A. Were beyond the limit of your capacities

- B. Were close to the limit of your capacities
- C. Had room to spare before you reached your limits
- D. Were taking it easy

20. Do you maintain a regular study schedule during school vacations?

A. Yes, most of the time

- B. Sometimes when I have to finish something
- C. I'll pick up a book but I don't "study"
D. I won't even touch a book on vacation
	- I won't even touch a book on vacation

21. Nowadays do you consider yourself to be

- A. Always easy going and relaxed
- B. Usually easy going
- C. Average--1 push enough to get what I need
- D. Pretty hard driving

22. Hhen taking an exam do you feel so tired from worrying that by the

time you take the test you almost don't care how well you do? A. Always C. Seldom B. Occasionally D. Never 23. As far as a sense of responsibility goes I am $-$ than the average student A. Much more responsible C. A little less responsible B. A little more responsible D. Much less responsible 24. Is it hard for you to do as well as you expect yourself to do? A. No, not ever **C.** Occasionally B. Not usually $D.$ Frequently 25. In general I approach life $\frac{1}{2}$ than the average student. A. Much more seriously C. A little less seriously
B. A little more seriously D. Much less seriously B. A little more seriously D. Much less seriously 26. Are you satisfied with your recent performance? A. Yes, very C. Not much

B. It's okay D. Not at a B. It's okay D. Not at all 27. How do you feel when you don't do as well as you expect to? A. Heartbroken--I tend to be lost for a while B. Hurt--I wonder why it didn't work out
C. Not too bad--I'll get another chance Not too bad- $-1'11$ get another chance D. I really don't worry about it $28.$ In being precise and careful about detail, I am $-$ than the average student. A. Much more precise **c.** A little less precise B. A little more precise D. Much less precise 29. Do you believe there's nothing you can't do if you work at it? A. Yes, definitely B. Most of the time c. It works that way once in a while D. No, it never works out that way for me 30. In the amount of effort put forth I give ------ than the average student. A Much more effort C. A little less effort B. A little more effort D. Much less effort

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APPENDIX J

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*XCT*E: Please enclose protocol, questionnaire and/or survey form
with this form. Human Investigation Committee approval
is valid for <u>one</u> year only.

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A Description of an Application of the Rasch One Parameter Latent Trait Model to the Student Version of the Jenkins Activity Survey

2. PRINCIPAL INVESTIGATOR/ACTIVITY DIRECTOR/FELLOW

Holm, Karyn

3. DECLARATION THAT HUMAN SUBJECTS EITHER WOULD OR WOULD NOT BE INVOLVED

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APPROVAL SHEET

The dissertation submitted by Karyn Holm has been read and approved by the following committee:

Dr. Jack A. Kavanagh, Director Associate Professor and Chairman, Foundations, Loyola

Dr. Samuel T. Mayo Professor, Foundations, Loyola

Dr. Ronald R. Morgan Associate Professor, Foundations, Loyola

The final copies have been examined by the director of the dissertation and the signature which appears below verifies the fact that any necessary changes have been incorporated and that the dissertation is now given final approval by the Committee with reference to content and form.

The dissertation is therefore accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy.

11/11/79

Date Director's Signature