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THE PREDICTION OF JOB ABILITY REQUIREMENTS USING ATTRIBUTE DATA BASED UPON THE POSITION ANALYSIS QUESTIONNAIRE (PAQ)

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20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

During recent years a number of investigators have suggested an alternative to the use of traditional validation procedures for validating personnel selection test procedures. In those situations where traditional validation is difficult or impossible to apply, investigators suggest the use of a procedure which has most recently been terms "job component validity." A number of different approaches to job component validity have been used, and in general, research relating to job component validity has revealed sub-

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stantial promise. The various approaches used have included the use of data relating to the Position Analysis Questionnaire (PAQ) as the basis for deriving estimates of the aptitude requirements of jobs. The PAQ is a structured job analysis procedure which provides for the analysis of jobs in terms of 187 job elements, using appropriate rating scales. The ratings on the individual elements, in turn, can be used to derive scores on several job dimensions (technically these are principal components resulting from the principal component analysis of PAQ data for a sample of jobs.)

Two methods of using PAQ-based data have been previously used in the job component validity framework. One of these consisted of the use of statistically identified job dimension scores for individual jobs as the direct basis for deriving estimates of aptitude requirements expressed in terms of scores on nine aptitude tests. This method proved to be reasonably satisfactory.

The other method consisted of the use of ratings of the relevance of each of many human "attributes" to each of the individual job elements of the PAQ. This basic procedure consisted of the use of "attribute-based" data in combination with "job analysis" data for individual jobs as the basis for deriving estimates of the aptitude requirements of the jobs in question. In the previous research with this approach a limited number of methods were used in combining the attribute data (the ratings on individual attributes for the job elements, or attribute dimensions based on these ratings) and the job analysis data (the ratings of the job elements for individual jobs or job dimensions based on such ratings). Previous research with such "attribute-based" data indicated that such estimates were reasonably valid for prediction of the requirements on cognitive tests, moderately valid with perceptual tests, but not useful with psychomotor tests.

The present study dealt with the exploration of various alternative methods of combining the "attribute-based" data with the "job analysis" data to derive estimates of job aptitude requirements. Special attention was focused on the prediction of psychomotor test requirements.

Twenty-one methods of combining these two sets of data were investigated. The findings generally confirm the results of the previous study using such attribute data in indicating reasonably satisfactory prediction with cognitive tests, moderate prediction with perceptual tests, and poor prediction in the case of psychomotor tests. There were however, some variations in the effectiveness of the different methods in predicting aptitude requirements, with some of the methods being differentially effective in the prediction of such requirements with different types of tests.

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INTRODUCTION

Since the establishment of the Equal Employment Opportunity Commission in 1964, the methods and practices used in the selection and validation of personnel testing instruments have come under increasing scrutiny by both the federal government and personnel psychologists. The study of personnel selection instruments is no longer simply an economic and scientific matter, but has, in recent years, become one of social, political, and judicial importance.

With the precedent set by the Griggs vs the Duke Power Company (Supreme Court, 1971), the personnel psychologist is no longer faced simply with devising test batteries which seem to work relatively well. He must now also be on a position to present evidence regarding the validity of these tests which is thorough enough to permit judgements by the courts as to the ability of the tests to make predictions concerning the future work behavior of employees (Fincher, 1973).

Probably the most widely accepted means by which the personnel psychologist can obtain such "evidence" is through the use of criterion related validation procedures. Criterion related validation involves the determination that a significant relationship exists between (1) a predictor or set of predictors, e.g. scores on some type of test(s), and (2) a criterion, e.g. some objective measure of performance such as the number of units produced per hour, or a more subjective measure of performance such as supervisory ratings. If criterion related validity is established, one would find that those individuals who have high predictor scores, do, in fact, show higher levels of job performance than do persons who have low scores on the predictor. Thus, such a predictor or set of predictors would be considered to provide valid estimates of the future job performance of job candidates.

Though empirical criterion related validation procedures might be the most desirable approach for evaluating personnel selection instruments, Balma (1959) notes that such traditional validation poses a number of practical problems for the industrial psychologist. Among these are:

(1) too few people on a particular job to carry out an empirical study,

(2) insufficient time for use of the "follow-up" method of validation and at the same time resistance of employees and unions to the "present employee method" of validation,

(3) great variability of job content of jobs with the same title,

(4) a rapid rate of change in job content within a given job,

(5) an increased number of jobs necessitated by automazation and computerization,

(6) a shortage of professional personnel to carry out an empirical study, and

(7) the time and cost involved in a traditional validation study.

As a result of the difficulties caused by these and other problems associated with the use of traditional validation procedures, a number of authors have suggested that an alternative approach to validation, based upon the use of job analysis data, be used in those situations where empirical, criterion related validation procedures are impractical. Lawshe (1952) introduced this alternative into the psychological literature under the name of "synthetic valdity." Lawshe used the term to denote the "inferring of valididty in a specific situation." Balma (1959) expanded Lawshe's definition somewhat by stating that synthetic validity refers to an "inferring of validity in one situation from a logical analysis of jobs into their elements, a determination of test validities for these elements, and combination of element validities into a whole." McCormick (1959), referring to the concept as "indirect validity," notes that such a process requires the validation of tests or other predictors on jobs which have certain characteristics in common, and the extention of these validities to similar jobs. McCormick has subsequently renamed the concept "job component validity" in the hope that this would alleviate any confusion caused by the term "synthetic validity"---it is, after all, not the validity which is synthesized, but is, instead, the test battery which is established by synthetic means.

Job Component Validity Methodology

A number of methodologies have been developed for use with the concept of job component validity (Balma, 1959; Drewes, 1961; and McCormick, 1974). Each of these methodologies has certain advantages and disadvantages associated with it.

Two methods, in particular, have been used with the Position Analysis Questionnaire (PAQ) (Jeanneret and McCormick, 1969; and Mecham, 1970). The PAQ is a structured job analysis instrument which provides for the analsyis of individual jobs in terms of each of 194 PAQ job elements. Most of the job elements provide for use of 6-point ratings scales of the relevance of the job elements to individual jobs. One of the methods consisted of the use of "job analysis" data as the basis for deriving estimates of the aptitude requirements of individual jobs. As applied to any given job, this approach consisted of the use of scores for the job on several "job dimensions" as the direct basis for deriving estimates of the predicted "mean test scores" of a sample of job incumbents. These predictions are made in terms of the nine tests of the General Aptitude Test Battery (GATB) of the United States Training and Employment Service. The job dimensions used in this approach are actually components resulting from the principal components analysis of PAQ data for a sample of jobs.

Research thus far has indicated that this particular appraoch has worked relatively well in predicting aptitude requirements, and thus would seem to have considerable utility in terms of the concept of job component validity. Mecham (1970), however, has made the comment that this approach does not provide very much "flexibility" in an operational sense, and has suggested that other possible methods might provide greater operational flexibility.

The second job component validity method that has been explored with the PAQ is based on the use of "attribute data" as related to the job elements of the PAQ. The basic attribute data consist of the rated "attribute requirements" of the PAQ elements, such ratings having been made by psychologists for each of 49 "aptitudes" and 27 "situational" variables that have been considered to be potentially relevant to the world of work. (The situational variables consist of descriptions of work situations to which job incumbents presumably have to "adjust," such as "varied duties," "dealing with people," and " working alone." They are considered to have implications in terms of personality, temperament, and interest factors.) The median ratings on these attributes for any given job element comprise an "attribute profile" for that attribute. Given a particular job, it has been postulated that the use of "attribute-based" data in combination with "job analysis" data might serve as the basis for "building up" an estimate of the total aptitude requirements for the job in question. Such a combination has involved the use of ratings on individual attributes and of "attribute dimensions" based on these ratings, and of ratings (for individual jobs) on the job elements and "job dimensions" based on such ratings.

While such an approach would appear to be potentially useful as the basis for deriving estimates of aptitude requirements of jobs in a job component validity framework, the results of a previous investigation (Mecham, 1970) have not been particularly encouraging. Although this approach was reasonably satisfactory in estimating requirements of cognitive abilities, and moderately so for perceptual abilities, it was not effective in estimating psychomotor requirements. In exploring such an approach, however, there are various ways in which the "attribute-based" data and the "job analysis" data might be combined to derive a "composite" estimate of requirements of various human attributes for individual jobs.

Purpose of the Present Study

The present study was directed towards the further exploration of the use of attribute ratings as the basis for establishing the job component validity of tests, in particular by using different methods of combining "attribute-based" data with "job analysis" data to form estimates of the aptitude requirements of jobs. The primary focus of this study related to the use of attribute data for deriving estimates of requirements for psychomotor tests, since the previous use of attribute data with such tests had proved to be ineffective.

METHOD

Several distinct methods of arriving at job ability requirements were explored. However, in all cases, the same job sample and criteria were used.

Job Sample

The sample used in the present study was identical to that used in an earlier investigation involving the Position Analysis Questionnaire and the estimation of job ability requirements via the job component validity paradigm (Marquardt, 1974). The original data pool consisted of over 8000 jobs for which PAQ analyses were availible. From this pool, 659 jobs were selected for which the U.S. Training and Employment Service (USTES) had normative and validity data on the GATB availible. These 659 jobs actually represent 659 positions on 141 distinct jobs which in turn represent 125 different sets of GATB normative and validity data. The redution from 141 to 125 is a result of the fact that the USTES had previously determined that certain jobs were essentially the same in terms of their basic characteristics, and were thus collapsed together in the reporting of the GATB data.

Criterion Data

Validation of a procedure used as part of a job component validity paradigm would ideally require the following:

(1) empirical data indicating the types and levels of abilities necessary to perform each of the activities included on a job analysis device,

(2) a job analysis which indicates the degree to which each of the activities incorporated in the job analysis device is involved in the performance of any job,

(3) a method by which the job analysis and ability data can be combined to estimate the specific ability requirements of any job, and

(4) some form of objective data representing the actual ability requirements of the job with which to compare the ability estimates derived in step #3.

In the present study the "objective data" mentioned above were in the form of the General Aptitude Test Battery normative and validity data which had been collected by the U.S. Training and Employment Service. Such data had been collected for 450 distinct jobs. These data include several thousand positions distributed over a large number of companies. The data were collected as part of concurrent validation studies, and thus these GATB scores represent the scores of incumbent employees who had not been selected for the job as a result of their test scores.

The primary assumption underlying the use of these data to represent the actual ability requirements of a job, is that employees tend to "gravitate" into those jobs on which they can achieve some reasonably successful degree of performance (McCormick and Tiffin, 1974). Shartle (1959) and Blum and Naylor (1968) report data which seem to lend some support to this assumption. This assumption implies that, for any GATB test, the normative and/or validity data of the incumbent employees on various jobs represent the relative importance to the job of that quality which is measured by the test. To the extent that the GATB data have not been influenced by the preselection procedures used by the companies involved, and to the extent that the employees have indeed gravitated to jobs in which they can perform successfully (and thus mean scores based on these incumbents indicate the level of various aptitudes necessary for successful performance), then the GATB data do represent the "actual" ability requirements of the jobs in the sample.

In the present study three different criteria based on availible GATB data were used. The first criterion used to evaluate the predictive effectiveness of the various component validity procedures used in estimating job ability requirements was the mean score on each of nine tests of incumbents on each of the jobs in the sample. These tests were those of the General Aptitude Tests Battery (GATB) of the United States Training and Employment Service. (These tests are as follows: G, general intelligence; V, verbal ability; N, numerical ability; S, spatial ability; P, form perception; Q, clerical ability;

K, motor coordination; F, finger dexterity; and M, manual dexterity.) Since one might suggest that a mean score on a GATB test of incumbents on a given job does not adequately represent the minimum level of an ability necessary for successful job performance, a second criterion was utilized. This criterion was, in effect, a "potential cutoff" score one standard deviation below the mean of the incumbents on a job. Such a value might then represent a more minimum level of an ability necessary for job performance. The third criterion used was the validity coefficient associated with each of the tests of the GATB. The validity data provided a conceptually different source of criterion data as compared to the other two crtieria.

Data Used as Predictors

In the previous section concerning the criteria used in the study, four steps were stated as necessary to establish the validity of a particular method for estimating the ability requirements of a paricular job. Step 1 through step 3 involve those procedures necessary to develop predictors under the job component validity paradigm.

As indicated earlier, ratings concerning the types and levels of 76 human "attributes" needed to perform each of the job elements of the PAQ were obtained as part of an earlier study (Marquardt, 1972). Between 8 and 11 raters rated each attribute. The median rating of each attribute as related to each of the PAQ job elements was used to represent the level of the attribute necessary to perform the particular activity denoted by the job element.

For each of the 659 jobs in the sample, there were availible PAQ analyses which indicated the degree to each each of the job elements of the PAQ was involved in the performance of the job. In certain methods used in the study, rather than using the ratings on individual PAQ elements to represent the various levels on each activity, the individual ratings were transformed into job dimension scores which indicated the degree to which a particular category of behaviors (dimension) was necessary to perform the job in question.

The primary purpose of this study was to explore the potential use of various methods by which job analysis data could be combined with the attribute data to provide estimates of the ability levels necessary for successful job performance. (Note that, in general terms, the "attributes" and "abilities" dealt with in this study are more technically referred to as "aptitudes.") As part of the initial phase of this study, 17 different approaches were used to collect information for use in estimating the ability requirements of jobs. These 17 approaches actually represented 21 distinct methods of deriving job ability requirement estimates. Of these 21 methods, 18 derived estimates in terms of individual human attributes. Thus they would give us scores in terms of such attributes as "verbal comprehension" or "static strength." The other three methods yielded scores on "attribute dimensions" rather than individual attributes. The various methods used in this study are discussed below.

Cross-product methods using individual PAQ ratings and attribute data. Conceptually it would seem reasonable to suggest that (1) given a particular attribute which has been judged to be of a specified level of importance to a job element, and (2) given that each such job element has been rated as to its importance to the job, then by combining these two ratings, we could get some indication of the degree of importance a particular attribute has for a given job. Multiplying these two forms of information as relating to any individual job would seem to be a logical way to "combine" these data. Assuming that such cross-product scores are meaningful when considering a single job element and attribute combination, the question then arises as to how one might evaluate the importance of a specific attribute when a number of job elements are involved in the job.

For each of the 659 jobs in the sample, three cross-product matrices were computed, and information from each of these was used as the basis for estimating the job ability requirements of each job. For any given job, the first such matrix (FULLXP) consisted of the cross-products (XP's) of the job analysis ratings on 182 job elements[1] as related to the job, and the median ratings on each of those elements on 49 aptitudinal attributes. Table 1 presents example derivations of the FULLXP matrix as well as the other two matrices, using five hypothetical job elements and four attributes.

1 Twelve PAQ elements were omitted because they were "open-ended" or because they dealt with pay/income.

For each of the 659 jobs in the sample, there existed a FULLXP matrix computed for 182 job elements and 49 attributes. Using this matrix, the following information was obtained on each job for each attribute:

--Method 1, the sum of the cross-products (SUMXP)

--Method 2, the mean of the cross-products (MEANXP)

--Method 3, the number of XP's above the grand mean XP where the grand mean XP= $\Sigma_i \Sigma_j$ XP/N, where i=1,...182 job elements, j=1,...659 jobs in the sample, and N=182 X 659 (ABOVE)

--Method 4, the number of XP's below the grand mean (BELOW)

--Method 5, the ratio of ABOVE/BELOW

--Method 6, the percent of XP's which fell into four of five quintiles where quintile 2 (6a)= 5.5-10.0 (PCT 2); quintile 3 (6a)= 10.5-15.0 (PCT 3); quintile 4 (6c)= 15.5-20.0 (PCT 4); and quintile 5 (6d)= 20.5-25.0 (PCT 5)

--Method 7, the sum of the XP's only for those attribute-element pairings where the PAQ job analysis rating= 5.0 (SUM5)

--Method 8, the mean of the XP's only for those attribute-element pairings where the PAQ job analsyis rating= 5.0 (MEAN5).

A second cross-product matrix (R1XP) was also computed for each of the jobs in the sample. This matrix was, in effect, an abbreviated version of FULLXP. In computing the R1XP matrix, cross-products were obtained for a particular attribute-element pairing <u>only if</u> the PAQ job analysis rating for the element involved was above a specified value. This value was the mean job analysis rating for that element as computed across all 659 jobs in the sample. In Table 1 the mean ratings for the five hypothetical job elements are 2.5, 2.0, 1.5, 1.5, and 4.0 respectively. Using this matrix, the following information was obtained on each job on each attribute:

--Method 9, the sum of the cross-products (R1SUM)

--Method 10, the mean of the cross-products (R1MEAN).

The final cross-product matrix (R2XP) computed for each job was a further abbreviation of FULLXP. In computing R2XP for each job, minimal standards were set for both the attribute ratings and the job analysis ratings before a cross product was actually computed. The standard used for the job analysis ratings was the same as that for the R1XP matrix, while the standard set for the attribute ratings was the mean rating for each attribute across all 182 PAQ job elements used in the study. For the four hypothetical attributes included in Table 1, these mean ratings are listed horizontally in the R2XP portion of the table. They are 2.0, 1.0, 2.0, and 2.5. The cross-product between a particular attribute-element pairing was computed only if both element and attribute ratings met the specified standards. From this R2XP matrix, the following information was obtained on each job on each of the 49 attributes:

--Method 11, the sum of the cross-products (R2SUM)

--Method 12, the mean of the cross-products (R2MEAN)

--Method 13, the number of XP's actually computed (R2NUM).

The rationale behind the use of these three types of matrices is relatively straightforward. Information obtained from the FULLXP matrix represents estimates of job ability requirements which conceptualize ability levels as being influenced by the level of a particular attribute on <u>each</u> of the 182 job elements of the PAQ (information obtained only when PAQ ratings= 5.0 is an exception to this statement). R1XP represents a method by which estimates of job ability requirements are made on the basis of information related to only the most important elements in the job. Ability levels required for the performance of unimportant job behaviors are ignored. The use of the final matrix, R2XP, takes into account the fact that, while particular abilities might be needed at some minimal level in order to perform most activities (and thus most individuals posses at least this minimum level), only when the level on a particular job exceeds this value, does this ability for that behavior enter into the estimation of job ability requirements.

<u>Methods using attribute dimension data</u>. Two sets of Q-type attribute dimensions were used in the present study. Marquardt (1974) extracted 23 attribute dimensions based upon a Q-type principal components analysis of the elements in each of the six major divisions

Table 1
Example Derivations of three Cross-Product Matrices (FULLXP, R1XP, and R2XP) Based Upon Hypothetical Ratings of Four Attributes and of Five PAQ Job Elements

Hypothetical PAQ Ratings Based on Analysis of Job X	Median Attribute Ratings for Job Elements of the PAQ: Attribute 1	2	3	4	Matrix Resulting From FULLXP Computation: Attribute 1	2	3	4	Mean Job Element Rating Across 659 Jobs*		Matrix Resulting From R1XP Computation: Attribute 1	2	3	4		Matrix Resulting From R2XP Computation: Attribute and Mean Rating*** 1 (2.0***)	2 (1.0***)	3 (2.0***)	4 (2.[illegible]***)
#1 2	5	2	3	1	10	4	6	2	2.5		X	X	X	X		X	X	X	X
#2 [illegible]	2	1	4	1	6	3	12	3	2.0		6	3	12	3		6	3	12	X
#3 [illegible]	1	1	5	3	5	5	25	15	1.5		5	5	25	15		X	5	25	15
#4 [illegible]	5	4	1	2	5	4	1	2	1.5		X	X	X	X		X	X	X	X
#5 5	3	5	2	4	15	25	10	20	4.0		15	25	10	20		15	25	10	20
Sum of the XP's (1)					41	41	54	43		(9)	26	23	47	38	(11)	21	23	47	35
Mean of the XP's (2)					8.2	8.2	10.9	8.6		(10)	8.7	7.7	15.7	12.7	(12)	10.5	7.7	15.7	17.5
# of XP's Above Grand Mean (3)					1	1	2	2			-	-	-	-		-	-	-	-
# of XP's Below Grand Mean (4)					3	4	2	3			-	-	-	-		-	-	-	-
Ratio of XP's Above/Below (5)					.3	.3	.5	.7			-	-	-	-		-	-	-	-
Percent in Quintile 1					.6	.8	.2	.6			-	-	-	-		-	-	-	-
Percent in Quintile 2 (6a)					.2	.0	.4	.0			-	-	-	-		-	-	-	-
Percent in Quintile 3 (6b)					.2	.0	.2	.2			-	-	-	-		-	-	-	-
Percent in Quintile 4 (6c)					.0	.0	.0	.2			-	-	-	-		-	-	-	-
Percent in Quintile 5 (6d)					.0	.2	.2	.0			-	-	-	-		-	-	-	-
Sum XP's, PAQ Rating = 5 (7)					20	30	35	35			-	-	-	-		-	-	-	-
Mean XP's, PAQ Rating = 5 (8)					10	15	17.5	17.5			-	-	-	-		-	-	-	-
# of XP's Computed					-	-	-	-			-	-	-	-	(13)	2	3	3	2

* The mean job element rating as computed across 659 jobs, used in computing R1XP and R2XP.

** The numbers in parentheses indicate the method of estimation which these data represent (Note: Percent in Quintile 1 was not used in the analyses of the data.)

*** The number for each attribute represents the mean rating for that attribute across 182 job elements used in computing R2XP.

of the PAQ and the ratings of these elements across 71 aptitudinal and situational attributes. As part of the present study, a new set of 17 aptitudinal attribute dimensions were developed using a procedure similar to that used by Marquardt (1974) but involving only 49 aptitudinal attributes. It was felt that such dimensions based solely on aptitudinal data would provide a better means for predicting the "aptitudinal" tests of the GATB.

Using these two sets of attribute dimensions, it was possible to generate an attribute score for any of the 20 attributes to be used in the study. Only 20 of the 49 attributes were used directly in the study since some of the attributes on the original list of 49 did not closely "match" the types of aptitudes tapped by the GATB tests. The scores on the attributes resulted in a job attribute profile for any given job. These profiles were generated using a three step procedure:

(1) the development of dimension attribute profiles. For each of the attribute dimensions (23 or 17) a profile of scores across the 20 attributes was derived. These profiles consisted of the component scores of the 20 attributes as derived from loadings of the job elements on the dimensions. The result of this process was that, for each of the 23 or 17 dimensions, there existed a quantitative value for each of the 20 attributes, these values being considered as comprising the attribute profile for that dimension,

(2) the development of job dimension scores. Attribute dimension scores were derived for each of the 659 jobs in the sample on each of the 23 or 17 attribute dimensions. These dimension scores were in effect component scores in which the loadings of the job elements on each dimension and the ratings of the elements as they related to the specific job in question produced a score which reflected the involvement of the job in the job elements that dominated that dimension,

(3) the combination of attribute dimension profiles and job dimension scores. The above procedures give us an attribute dimension profile for each of the 23 or 17 attribute dimensions

an attribute dimension profile as well as a dimension score for any given job on each of the 23 or 17 dimensions. For any given job a job attribute dimension profile can be derived by taking the job dimension scores for each job and multiplying these scores across the values in the appropriate attribute dimension profile, and summing the resulting cross-product values for each attribute. This was done for each of the 659 jobs in the sample (see Table 2).

Table 2

Example Derivation of Job Attribute Dimension Profiles

Attribute Dimension	Dimension Score	Attribute Dimension Profile: Attributes				Cross-Product Values: Attributes			
		1	2	3....20		1	2	3....20	
1	2	1	2	5	1	2	4	10	2
2	1	3	4	0	2	3	4	0	2
⋮									
23 or 17	5	4	3	2	1	20	15	10	5
	job attribute dimension profile=					25	23	20	14

One set of R-type attribute dimensions was used in the present study. Marquardt (1973) extracted seven attribute dimensions based upon an R-type principal components analysis of 49 aptitudinal attributes and the ratings of each attribute across 182 PAQ job elements. Scores relating to these attribute dimensions were used to predict the GATB criterion data, and were also used in conjunction with scores on the Q-type dimensions in similar analyses. Dimension scores for these seven attribute dimensions were developed in a two step process:

(1) the development of element dimension values. These values were, in effect, the scores of the 182 job elements as derived from the loadings of each of the attributes on the seven

dimensions and the median ratings of each of the 182 elements on the appropriate attributes within each dimension. The result of this process yielded a vector of "dimension values" for each of the 182 PAQ job elements.

(2) the development of attribute dimension scores. An attribute dimension score was derived for each of the jobs in the sample for each of the seven R-type attribute dimensions. These scores were derived by multiplying the PAQ job analysis ratings across the appropriate element dimension values for each element (see Table 3).

Table 3
Example Derivation of R-type Dimension Scores

PAQ Ratings Based on Analysis of Job X		Element Dimension Values for Dimensions: 1	2	3	4	5	6	7	Cross-Product Score: Rating x Value 1	2	3	4	5	6	7
#1	U 2	3	1	0	0	4	2	0	6	2	0	0	8	4	0
#2	U 3	1	1	2	2	2	3	1	3	3	6	6	6	9	3
#3	U 2	3	3	3	4	0	1	2	6	6	6	8	0	2	4
⋮															
#182	S 0	3	4	5	4	3	1	2	0	0	0	0	0	0	0
								dimension scores=	15	11	12	14	14	15	7

The Combination of R-type and Q-type Attribute Dimension Data

The 17 new Q-type attribute dimensions were combined with the R-type attribute dimension data to form job attribute dimension values. The job attribute dimension values resulted from a combination of the loadings on the PAQ job elements associated with the Q-type attribute dimensions and the element dimension values as derived for the seven R-type attribute dimensions (see Table 4). The attribute dimension values were then multiplied by the appropriate Q-type attribute dimension scores and were then summed for each of the seven R-type dimensions across the 17 Q-type dimensions to form a set of job attribute dimension values.

Table 4

Example Derivation of Job Attribute Dimension Values

Dimension X PAQ Element Loadings		Element Dimension Values: Dimensions							Cross-Product Values: Dimensions						
		1	2	3	4	5	6	7	1	2	3	4	5	6	7
#1	0.5	3	1	0	0	4	2	0	1.5	0.5	0.0	0.0	2.0	1.0	0.0
#2	0.1	1	1	2	4	0	3	1	0.1	0.1	0.2	0.4	0.0	0.3	0.1
#3	0.9	2	2	3	1	1	0	0	1.8	1.8	2.7	0.9	0.9	0.0	0.0
⋮															
#182	0.6	5	1	3	1	0	0	0	3.0	0.6	1.8	0.6	0.0	0.0	0.0
attribute dimension values= for dimension X									6.4	3.0	4.7	1.9	2.9	1.3	0.1

The use of the attribute dimension data provided us with information based upon much larger units of worker behavior than did the use of individual PAQ job analysis ratings and attribute ratings. From these attribute dimensions the following data were used as estimates of the job ability requirements for each job in the sample:

--Method 14, job attribute dimension profiles based upon (14a) Marquardt's 23 attribute dimensions, and (14b) the new 17 attribute dimensions

--Method 15, dimension scores based upon the 17 new dimensions

--Method 16, dimension scores on the seven R-type dimensions

--Method 17, job attribute dimension values based upon the combination of the 17 new Q-type and seve R-type attribute dimensions.

The methods of estimation used in the present study can be viewed as representing essentially four different "models" for estimating job ability requirements. Two of the models are concerned with "how much" information is to be used in deriving ability requirement estimates, while the other two models relate to the complexity of the information used for making such estimates. In the first case one might conceptualize ability requirements as being determined by the degree to which a particular ability is required for <u>each</u> of the various work behaviors represented on the PAQ. Viewing the matter in such a way would imply that ability requirements are a result of a cumulative process. Given the 182 job elements of the PAQ, whether or not a particular ability is needed for successful job performance depends upon the "cumulative" importance of that ability across all of the PAQ job elements. This would represent the "cumulative" model of job ability requirements.

One might also suggest that ability requirements depend instead, upon the level of a particular attribute which is necessary for <u>only</u> those work behaviors which have been judged most crucial to the job. If for instance, one has a job in which the only important job behavior is "using written materials," the degree to which various attributes (e.g. verbal comprehension or finger dexterity) are necessary for successful job performance would depend upon the degree to which the various attributes are necesssary in using of the other 181 job elements. This would represent the "critical behaviors only" model for estimating job ability requirements.

Another aspect associated with the estimation of job ability requirements is the degree to which "micro" versus "macro" information about the jobs are used as the source of that estimation. In the present study, "micro" sources of information refer to the data for the individual job element ratings and the individual attributes as related to these job elements for the estimation of job ability requirements. The most commonly used method for combining these two sources of information has been to compute a cross product (XP) between the individual element job analysis rating and the attribute ratings associated with each element. This method was used in the present study. The information gained from the use of such cross products is "micro" in the sense that we are dealing with specific element-attribute pairings representing specific work behaviors.

On the other hand, job analysis and attribute dimension scores provide us with a form of "macro" information in that such dimensions are concerned with much more general classes of work activities. Previous studies using PAQ data in a job component validity paradigm have tended to rely heavily upon macro sources of job information, while the use of micro information might well provide the greatest long term benefits. The present study tested the relative effectiveness of micro and macro sources of information for use in the estimation of job ability requirements. Appendix A presents the 21 distinct methods of estimation used in the present study, as well as the "model" they represent, the abbreviation for each method used in this report, and a brief description of each method.

Phase I---Initial Analyses

Twenty of the 49 aptitudinal attributes were selected for use in the initial phase of the analysis. Since the GATB tests cover only a limited number of ability areas, those attributes which seemed most closely matched to abilities included in the GATB tests were used. The criteria used in the initial phase of this study were the mean test scores on the nine tests of the GATB, as well as the potential cutoff scores for those same nine tests. Earlier research (Mecham, 1970) had shown that prediction of validity coefficients was not particularly successful, and thus it was decided they would be used as criteria only after a number of the best methods for estimation had been selected.

Scores on the 20 attributes as derived by each of the various methods were correlated with both the mean and potential cutoff scores for each job on each of the nine tests of the GATB. These correlations between GATB data and attribute scores were transformed using Fisher's z-transformation so that they could be compared to one another using analysis of variance techniques. The GATB tests were then divided into three categories: (1) cognitive (G, general intelligence; V, verbal ability; and N, numerical ability); (2) perceptual (S, spatial ability; P, form perception; and Q, clerical perception); and (3) psychomotor (K, motor coordination; F, finger dexterity; and M, manual dexterity). Likewise the attributes were divided into three similar categories.

If the methods used to estimate job ability requirements were accurate, then cognitive attributes should have high positive correlations with the data from the cognitive GATB tests. Similarly, this relationship should hold between the perceptual attributes and the perceptual GATB tests, and the psychomotor attributes and the psychomotor GATB tests.

Since it would be possible for a particular method of estimation to accurately predict cognitive abilities while not doing nearly so well in predicting perceptual and psychomotor abilites, the various methods of estimation were compared to one another in terms of their effectiveness in predicting each of the three separate categories. Also, multiple regression analysis was carried out in order to compare the various methods in terms of their multiple correlations. From the data provided by these initial correlations between the attribute scores and the GATB test data (this included the multiple correlations between GATB data and the various attribute dimension scores), a number of methods which seemed to provide the "best" means for predicting job ability requirements were selected for use in the later phase of the analysis.

Phase II---Use of Validity Data and Adjustment of Criterion Scores

In phase two of the study, those methods for estimating job ability requirements which were deemed "best" among the numerous ones included in the initial phase were used in conjunction with two "new" criteria. First, scores derived by these methods for various attributes were correlated with validity data associated with the nine tests of the GATB.

Secondly, in phase two an attempt was made to deal with the problem associated with the criterion data used in this and previous studies, i.e. the GATB mean and potential cutoff scores. Adjustments were made to the criterion data in an attempt to take into account the high intercorrelations found between the mean cognitive and psychomotor GATB test scores. These adjusted scores were then used as a "new" criterion along with the validity data discussed above.

RESULTS

An initial phase of the study dealt with the development of new attribute dimensions based on Q-type principal components analyses of the six major divisions of the PAQ. Methods of estimating job ability requirements based upon these and other attribute dimensions, as well as cross-product data from the individual job analysis ratings of the PAQ job elements, and individual attribute ratings on these job elements were used in a job component validity paradigm. The results relating to the effectivenss of these various methods for estimating job ability requirements are presented in this section.

Principal Components Analysis Using Aptitudinal Attributes

In developing schemes based upon macro information for use in estimating job ability requirements, principal components analyses were carried out with the job elements within each of the six major divisions of the PAQ. Q-type principal components analyses were carried out using the correlation matrices computed using the 49 aptitudinal attributes and those elements in each of the six PAQ divisions.

In each of the six analyses, the diagonal elements in the correlation matrix were set to 1.0, and extraction of components terminated when the eigenvalues dropped below 1.0. The six analyses resulted in a total of 17 principal components. Descriptions of the 17 components are given in Appendix B. The job elements which received loadings on the various components of .45 or greater are presented in Appendices C,D,E,F,G, and H.

Estimation of Job Ability Requirements

A total of 21 diferent methods of estimating job ability requirements were used in this study. Eighteen of these methods produced estimates in terms of "attribute scores," i.e. for each of the 659 jobs in the sample, a score was derived for each of the 20 aptitudinal attributes, this score being computed using each of the 18 methods. Two methods produced estimates of job ability requirements in terms of "dimension scores." In these cases, for each of the 659 jobs in the sample, there were derived seven dimension scores (one for each of the seven R-type attribute dimensions). A final method also resulted in the derivation of estimates of ability requirements in terms of "dimension scores." However, in this case, there were seventeen scores derived for each job (one for each of the 17 new Q-type attribute dimensions). Criteria data used in this study included the mean test scores and potential cutoff scores of incumbents on jobs in the sample for the nine tests of the GATB. Validity coefficients associated with each of the nine tests for each of the jobs in the sample were also used as criterion data.

Correlational analysis. For 18 of the 21 methods of estimating job ability requirements, correlations were obtained between the attribute scores on each job for 20 attributes (Appendix I) as derived by each of the 18 methods, and the mean tests scores and cutoff scores on the nine tests of the GATB for incumbents on each of the 659 jobs in the sample. Three of the twenty-one methods used attribute dimension data as the basis for estimation of job ability requirements of the individual jobs, rather than scores on the 20 attributes, and thus were omitted from this part of the analysis.

In no instance did correlations between attribute scores and the criterion of potential cutoff scores differ by more than .03 higher or lower than correlations between attribute scores and the criterion of mean test scores. Therefore, in the remainder of this text, data reported will be only in terms of the mean test score data. Also note that in computing mean corrrelations between GATB test data and attribute scores as derived by the various methods, only those correlations involving attibutes which were felt to closely "match" the individual GATB tests were used in the computation of the mean (Appendix I). This was the case in all of the analyses carried out as part of this study. In Table 5 are presented the mean correlations (Fisher's z-transformation) for each of the 18 methods as computed across all of the tests within each of the four major categories of the GATB tests, i.e. cognitive tests (3-G,V,N); perceptual tests (3-S,P,Q); the motor coordination test (1-K); and psychomotor tests (2-F,M). Since correlations relating to the GATB test K were considerably different from the other two psychomotor tests (F and M), the mean correlations associated with this test were reported separately. From Table 5 note that while attribute scores derived by a number of methods correlate relatively well with the cognitive tests, correaltions for the perceptual tests were only moderate, and those for the psychomotor tests were extremely low. Correlations associated with the GATB test K were often negative in direction.

Multiple regression analysis. For all 21 methods, multiple correlations were computed between predictors (estimates of job ability requirements) based on the 21 methods, and the criteria of mean test scores and potential cutoff scores of incumbents on jobs in the sample for each of the nine GATB tests. Again, due to the similarity of results between the mean score and potential cutoff score data, data are presented only for the mean score criterion. For each of the 18 methods which derive prediction scores in terms of the 20 individual attributes, those attribute which seem to most closely match the abilities tapped by the individual GATB tests were used as predictors in the multiple regression analysis (Appendix J). For the two methods which provide estimates of ability requirements in terms of scores on the seven R-type attribute dimensions, all seven of the dimension scores were entered into the equations. The final method provided predictor scores in terms of the 17 Q-type attribute dimensions, and thus all 17 of the dimension scores were entered into the regression equations. The multiple correlations (z-transformed) between the various predictor scores and the mean scores of job incumbents on each of the nine GATB tests are given in Table 6.

Except for methods PCT2, SUM5, and MEAN5, multiple correaltions between predictors and the criterion of mean test scores were quite good for the G and V tests. Multiple correlations based on predictors from the attribute dimension data were quite high for the N,S,P,Q, and K tests. Multiple correlations f-- the F and M tests across all methods of estimation were quite lc

Table 5

Mean Correlations Between Estimates of Ability Requirements Derived By 18 Methods and Mean GATB Scores for Four GATB Test Categories

	Test Category			
Method	Cognitive	Perceptual	Motor Coordination	Psychomotor*
SUMXP	.33	-.02	-.21	.06
MEANXP	.42	.01	-.22	.10
ABOVE	.09	-.01	-.16	.04
BELOW	.09	-.01	-.16	-.04
ABOBEL	.08	-.01	-.17	.05
PCT2	-.03	-.02	-.09	.06
PCT3	.17	.08	-.03	.04
PCT4	.14	.08	.04	.06
PCT5	.13	.03	.04	.02
SUM5	.05	.07	.02	.07
MEAN5	.08	.09	.05	.04
R1SUM	.08	.10	-.11	.07
R1MEAN	.10	.14	.02	.07
R2SUM	.08	.10	-.10	.07
R2MEAN	.13	.15	.07	.08
R2NUM	.07	.06	-.13	.06
XMJADP	.32	.12	.23	-.03
XM17	.46	.15	-.05	.12

N=659 jobs

*N=617 jobs

Table 6

Multiple Correlations Between Estimates of Ability Requirements Derived By 21 Estimation Methods and Mean Test Scores of Job Incumbents on Nine GATB Tests

Method	G	V	N	S	P	Q	K	F*	M*
SUMXP	.68	.45	.31	.45	.52	.55	.68	.17	.21
MEANXP	.79	.63	.52	.52	.62	.65	.76	.18	.24
ABOVE	.71	.78	.26	.29	.39	.65	.30	.08	.12
BELOW	.71	.78	.26	.29	.39	.65	.30	.08	.12
ABOBEL	.66	.73	.26	.27	.35	.60	.31	.07	.11
PCT2	.28	.10	.08	.27	.33	.23	.17	.11	.13
PCT3	.56	.47	.18	.33	.32	.34	.37	.09	.12
PCT4	.54	.60	.13	.18	.19	.32	.20	.13	.13
PCT5	.65	.66	.38	.06	.14	.35	.21	.04	.05
SUM5	.33	.35	.11	.10	.11	.10	.18	.10	.10
MEAN5	.28	.29	.21	.14	.17	.16	.13	.12	.12
R1SUM	.62	.62	.11	.28	.23	.40	.41	.15	.20
R1MEAN	.60	.58	.16	.22	.29	.40	.41	.17	.22
R2SUM	.59	.58	.11	.29	.28	.44	.48	.16	.22
R2MEAN	.60	.52	.12	.30	.31	.37	.60	.12	.18
R2NUM	.46	.44	.11	.31	.30	.46	.63	.21	.27
XMJADP	.68	.65	.48	.45	.62	.68	.73	.09	.23
XM17	.76	.71	.52	.56	.65	.51	.81	.16	.24
NEW17	.89	.93	.89	.73	.69	.85	.87	.26	.28
SADAP	.81	.89	.83	.60	.63	.79	.81	.20	.26
BADAP	.83	.91	.83	.65	.65	.76	.79	.19	.23

N=659 jobs

* N=617 jobs

Comparison of "cumulative" vs "critical behaviors only" methods of estimation. As described earlier, those methods using data from the FULLXP matrix (except SUM5 and MEAN5) represent a model of predicting the required level of any given ability for a particular job as being influenced by the cumulative importance of that ability across a large number of job elements. Those methods based on data from the matrices R1XP and R2XP (as well as SUM5 and MEAN5) represent a model for predicting job ability requirements which views the requirements as depending upon the importance of a particular attribute only as it regards the most critical work behaviors found on the job.

The methods were divided into two groups according to this distinction. Using individual correlations between attribute scores as derived by the various methods on each of the 20 aptitudinal attributes and the mean test scores of job incumbents on each of the nine GATB tests, a one way analysis of variance was carried out between the two groups for each of the four conceptual divisions of the GATB (cognitive, perceptual, motor coordination, and psychomotor). The results of this analysis are given in Table 7.

The mean correlation between cognitive attribute scores and cognitive GATB test data for all the jobs in the sample as based upon the cumulative methods of estimation ($\bar{r}$=.16) was significantly higher than that based upon "critical behaviors only" methods ($\bar{r}$=.09). The reverse was the case when considering the relationship between perceptual attribute scores and perceptual GATB data. Admittedly, the statistical significance of the mean differences is due largely to the sample sizes involved. Practical significance is lacking in both instances. Neither cumulative or critical behavior methods adequately estimated ability requirements for the psychomotor tests data (F and M), and both models of estimation produced negative mean correlations when considering the GATB motor coordination test.

In an attempt to clarify the above inconclusive results, a one-way analysis of variance was carried out between the two models of estimation, this time using the multiple correlations on the mean scores of the GATB test for the various methods in each of the two models as the basis of the analysis. The results of the analsysis are presented in Table 8. When considering the multiple correlations across all nine GATB tests, the two models of prediction were not significantly different.

Table 7

ANOVA Based Upon Mean Correlations for "Cumulative" and "Critical Behaviors Only" Models for Deriving Job Ability Requirement Estimates

GATB Test	Cumulative			Critical					
Categories	Mean	SD	N	Mean	SD	N	df	F-ratio	p
Cognitive	.16	.18	216	.09	.08	168	1,382	22.47	.01
Perceptual	.02	.14	162	.10	.12	126	1,286	27.08	.01
Mot. Coord.	-.11	.15	54	-.02	.11	42	1, 94	8.77	.01
Psychomotor	.04	.05	108	.06	.04	84	1,190	8.02	.01

Table 8

ANOVA Based Upon Multiple Correlations for "Cumulative" and "Critical Behaviors Only" Models for Deriving Job Ability Requirement Estimates

Treatment group:	Cumulative	Critical Behaviors Only
Sample size:	81	63
Mean:	.36	.30
SD:	.22	.17

Source	SS	df	MS	F
Between groups	.1317	1	.1317	3.2647 NS
Within groups	5.7265	142	.0403	
Total	5.8582			

<u>Comparison of "micro" vs "macro" sources of job information.</u> The cumulative and critical behaviors only methods used in the above analysis represent "micro" sources of job information. In contrast to such methods are those "macro" methods of estimation based upon attribute dimension data. These two groups of methods, i.e. micro vs macro methods, were compared as to their relative effectiveness in estimating job ability requirements. For each method in each of the two groups, there had been obtained multiple correlations between the predictors derived by each particular method and the mean test scores of incumbents on the jobs in the sample for the nine tests of the GATB. These multiple correlations were used as the basis for a one-way analysis of variance between the two groups. The results of this analysis are given in Table 9.

Table 9

ANOVA for "Micro" Methods and "Macro" Methods of Estimation of Job Ability Requirements

Treatment group:	Micro Method	Macro Methods
Sample size:	144	45
Mean:	.33	.61
SD:	.20	.21

Source	SS	df	MS	F
Between groups	2.74	1	2.74	60.31**
Within groups	8.50	187	.05	
Total	11.25	188		

** p less than .01

When considering all nine tests of the GATB, there was a very dramatic difference between the two groups. Methods based upon macro sources of job information did significantly better than those using micro sources of job information. However, neither group did well in predicting the job ability requirements associated with the F and M tests of the GATB.

Selection of methods for use with validity data and adjusted mean test scores. Only those methods for which scores on each of the 20 individual attributes could be obtained were considered for use in Phase II of the analysis, in which validity data and adjusted GATB test score data were used. It was originally anticipated that such methods would have a greater long term benefit in terms of the flexibility and scope of any operational system using the job component validity paradigm. Since it had already been shown that there were, indeed, differences among the various methods in terms of their effectiveness in estimating job ability requirements, Newman-Keuls tests for the differences between all posible pairs of means were carried out for each of the four conceptual categories of the GATB data. The mean correlations between the attribute scores and the mean scores of job incumbents on the nine tests of the GATB were used as the basis of these analyses. The results of these analyses are given in Tables 10, 11,12, and 13. Four methods, R2MEAN, MEANXP, XMJADP, and XM17, were found to consistently rank near the top of the list of 18 methods in terms of their mean correlations in each of the four test categories, and were in many cases significantly different from those methods ranking below them. As a result, these four methods were selected for use in Phase II.

Prediction of validity coefficients. Correlations between scores derived on the various attributes and the criterion of validity coefficients for each of the sample jobs associated with the nine GATB tests were obtained. Mean correlations for the four methods of estimation in terms of the four categories of the GATB tests are presented in Table 14. The mean correlations were extremely low, thus indicating that no method had potential utility for predicting the criterion of validity coefficients.

Adjustment of criterion data. In order to take into account the rather high intercorrelations between the mean GATB test scores of incumbents on jobs used in the sample, a method was needed which would enable us to determine the degree to which these high intercorrelations had resulted in the mean test scores being inflated (or perhaps deflated)

Table 10

Newman-Keuls Test Based Upon Differences Between the Mean Correlations for the GATB Cognitive Tests on 18 Methods of Estimating Job Ability Requirements

Ranked Means	XM17	MEANXP	SUMXP	XMJADP	PCT3	PCT4	PCT5	R2MEAN	R1MEAN	ABOVE	BELOW	R2SUM	ABOBEL	MEANS	R1SUM	R2NUM	SUM5	PCT2
XM17		.04	.13**	.14**	.29**	.32**	.32**	.32**	.36**	.37**	.37**	.38**	.39**	.38**	.38**	.38**	.41**	.46**
MEANXP			.09**	.10**	.25**	.28**	.28**	.28**	.32**	.33**	.33**	.34**	.34**	.34**	.34**	.34**	.37**	.44**
SUMXP				.01	.16**	.19**	.19**	.19**	.23**	.24**	.24**	.25**	.25**	.25**	.25**	.25**	.26**	.35**
XMJADP					.16**	.18**	.19**	.19**	.22**	.24**	.24**	.24**	.24**	.24**	.25**	.25**	.27**	.35**
PCT3						.02	.03	.03	.06	.08	.08	.03	.09	.09	.09	.09	.11**	.19**
PCT4							.01	.01	.04	.06	.06	.06	.07	.07	.07	.07	.09	.17**
PCT5								.00	.03	.05	.05	.05	.06	.06	.06	.06	.08	.16**
R2MEAN									.03	.05	.05	.05	.06	.06	.06	.06	.08	.16**
R1MEAN										.02	.02	.02	.03	.03	.03	.03	.05	.13**
ABOVE											.00	.01	.01	.01	.01	.01	.03	.11*
BELOW												.01	.01	.01	.01	.01	.03	.11*
R2SUM													.00	.00	.00	.01	.03	.11*
ABOBEL														.00	.00	.00	.03	.10*
MEANS															.00	.00	.03	.10*
R1SUM																.00	.02	.10*
R2NUM																	.02	.10*
SUM5																		.08*
PCT2																		

* p less than .05

** p less than .01

Table 11

Newman-Keuls Test Based Upon Differences Between the Mean Correlations for the GATB Perceptual Tests on 18 Methods of Estimating Job Ability Requirements

Ranked Means	R2MEAN	XM17	R1MEAN	XMJADP	R1SUM	MEANS	R2SUM	PCT4	PCT3	SUM5	R2NUM	PCT5	MEANXP	BELOW	ABOVE	ABOBEL	PCT2	SUMXP
R2MEAN		.00	.01	.03	.06	.06	.06	.07	.08	.09	.09	.12	.14	.16	.16	.16	.17	.17
XM17			.01	.03	.05	.06	.06	.07	.08	.09	.09	.12	.13	.16	.16	.16	.17	.17
R1MEAN				.02	.05	.05	.05	.06	.07	.07	.07	.11	.13	.15	.15	.15	.16	.16
XMJADP					.03	.03	.03	.04	.05	.06	.06	.09	.11	.13	.13	.13	.14	.14
R1SUM						.01	.01	.02	.02	.03	.03	.07	.08	.10	.10	.11	.11	.11
MEANS							.00	.01	.02	.03	.03	.06	.08	.10	.10	.10	.11	.11
R2SUM								.01	.01	.02	.03	.06	.07	.10	.10	.10	.11	.11
PCT4									.00	.01	.01	.05	.06	.08	.08	.09	.09	.10
PCT3										.01	.01	.05	.06	.08	.08	.09	.09	.09
SUM5											.00	.04	.05	.07	.07	.03	.09	.08
R2NUM												.03	.05	.07	.07	.07	.08	.08
PCT5													.01	.04	.04	.04	.05	.05
MEANXP														.02	.02	.03	.03	.03
BELOW															.00	.00	.01	.01
ABOVE																.00	.01	.01
ABOBEL																	.00	.01
PCT2																		.00
SUMXP																		

There were no significant differences between means.

Table 12

Newman-Keuls Test Based Upon Differences Between the Mean Correlations for the GATB Psychomotor Tests on 18 Methods of Estimating Job Ability Requirements

Ranked Means	XM17	MEANXP	R2MEAN	R1MEAN	R1SUM	SUM5	R2SUM	PCT2	SUMXP	PCT4	R2NUM	ABOBEL	MEAN5	ABOVE	PCT3	PCT5	XMJADP	BELOW
XM17		.02	.04*	.05*	.05*	.05*	.06*	.06*	.06*	.06*	.07**	.07**	.08**	.08**	.08**	.10**	.15**	.17**
MEANXP			.03	.03	.03	.04	.04	.04	.04	.05	.05	.06	.06	.06	.06	.09**	.14**	.15**
R2MEAN				.01	.01	.01	.01	.01	.02	.02	.02	.03	.03	.03	.03	.06	.11**	.12**
R1MEAN					.00	.01	.01	.01	.01	.01	.02	.02	.03	.03	.03	.06	.10**	.12**
R1SUM						.00	.00	.01	.01	.01	.02	.02	.03	.03	.03	.05	.10**	.11**
SUM5							.00	.00	.01	.01	.01	.02	.02	.02	.02	.05	.10**	.11**
R2SUM								.00	.00	.01	.01	.02	.02	.02	.02	.05	.10**	.11**
PCT2									.00	.01	.01	.02	.02	.02	.02	.05	.09**	.11**
SUMXP										.00	.01	.01	.02	.02	.02	.05	.09**	.10**
PCT4											.00	.01	.01	.01	.02	.04	.09**	.10**
R2NUM												.01	.01	.01	.01	.04	.09**	.10**
ABOBEL													.00	.00	.01	.03	.08**	.09**
MEAN5														.00	.00	.03	.08**	.09**
ABOVE															.00	.03	.08**	.09**
PCT3																.03	.08**	.09**
PCT5																	.05**	.06**
XMJADP																		.01
BELOW																		

* p less than .05

** p less than .01

Table 13

Newman-Keuls Test Based Upon Differences Between the Mean Correlations for the GATB Motor Coordination Test on 18 Methods of Estimating Job Ability Requirements

Ranked Means	XMJADP	R2MEAN	MEAN5	PCT4	PCT5	R1MEAN	SUM5	PCT3	XM17	PCT2	R2SUM	R1SUM	R2NUM	ABOVE	BELOW	ABOBEL	SUMXP	MEANXP
XMJADP		.16	.18	.18	.19	.21	.21	.26*	.28**	.31**	.32**	.33**	.35**	.39**	.39**	.39**	.44**	.44**
R2MEAN			.02	.02	.03	.05	.05	.10	.12	.15	.16	.17	.19	.23	.23	.23	.28**	.28**
MEAN5				.01	.01	.03	.03	.08	.10	.14	.15	.16	.18	.21	.21	.22	.26	.26
PCT4					.01	.02	.03	.07	.10	.13	.14	.15	.17	.21	.21	.21	.26	.26
PCT5						.02	.02	.07	.09	.12	.13	.15	.16	.20	.20	.20	.25	.25
R1MEAN							.00	.05	.07	.11	.12	.13	.15	.18	.18	.19	.23	.24
SUM5								.05	.07	.10	.11	.12	.14	.18	.18	.18	.23	.23
PCT3									.02	.06	.07	.08	.10	.13	.13	.14	.16	.19
XM17										.03	.04	.05	.07	.11	.11	.11	.16	.16
PCT2											.01	.02	.04	.08	.08	.08	.13	.13
R2SUM												.01	.03	.07	.07	.07	.12	.12
R1SUM													.02	.06	.06	.06	.11	.11
R2NUM														.04	.04	.04	.09	.06
ABOVE															.00	.00	.05	.05
BELOW																.00	.05	.05
ABOBEL																	.05	.05
SUMXP																		.00
MEANXP																		

* p less than .05

** p less than .01

Table 14

Mean Correlations Between Attribute Scores and the Criterion of Validity Coefficients for Four Methods of Estimation on Four GATB Test Categories

	GATB Category			
Method	Cognitive	Perceptual	Motor Coordination	Psychomotor
XMJADP	.08	.03	-.04	-.12
XM17	.10	.06	-.06	-.05
R2MEAN	.06	.07	-.03	-.03
MEANXP	.12	.12	-.06	.02

from what they would have been had the intercorrelations of the mean test scores had been relatively the same as those for individual test scores (Table 15). To do this, two sets of regression equations were calculated for each test of the GATB, with the other eight tests being used as predictors of the particular mean test score. One set of equations was computed using the intercorrelation matrix of the mean scores on the GATB tests as calculated from the sample data on 659 job. The second set of equations was computed using the intercorrelation matrix as calculated from the "population" data based on test scores of individuals on approximately 23,000 jobs. Thus for each GATB test there existed a sample regression equation and a population regression equation made up of the beta weights for the other eight tests being used as predictors (see Appendix K).

For each of the 659 jobs in the sample, predictions on the motor coordination, finger dexterity, and manual dexterity test scores associated with that job were made, one using the sample regression equation and the other using the population regression equation. A "difference" score was calculated between the two predictions for each

Table 15

Population and Sample Test Score

Intercorrelations for Nine GATB Tests

Population data: individual test score, N≐23,000

Test	G	V	N	S	P	Q	K	F	M
G	1.00								
V	.84	1.00							
N	.86	.67	1.00						
S	.74	.46	.51	1.00					
P	.61	.47	.58	.59	1.00				
Q	.64	.62	.66	.39	.65	1.00			
K	.36	.37	.41	.20	.45	.51	1.00		
F	.25	.17	.24	.29	.42	.32	.37	1.00	
M	.19	.10	.21	.21	.37	.26	.46	.52	1.00

Sample data: mean test scores for incumbents, N=659 jobs

Test	G	V	N	S	P	Q	K	F	M
G	1.00								
V	.93	1.00							
N	.97	.89	1.00						
S	.89	.71	.83	1.00					
P	.83	.73	.83	.83	1.00				
Q	.81	.87	.82	.62	.84	1.00			
K	.76	.83	.78	.59	.81	.90	1.00		
F	.59	.55	.61	.56	.76	.64	.71	1.00	
M	.41	.32	.45	.46	.61	.46	.56	.70	1.00

job on each of the three tests. The actual mean test score for a given job on a given GATB test was adjusted upwards by that amount if the sample prediction was less than the population prediction, or was adjusted downward by that difference if the sample prediction was higher than the population prediction. Correlations between attribute scores and the adjusted GATB mean test scores were obtained in a manner similar to that used in the initial correlational analysis using the unadjusted means. Presented in Table 16 are the mean correaltions for the four estimation methods used in Phase II, in terms of both adjusted and unadjusted mean test scores.

Table 16

Mean Correlations Between Attribute Scores and the Criterion of Adjusted and Unadjusted Mean Test Scores on Three GATB Tests

	Test					
	K		F		M	
Method	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted
R2MEAN	.10	.06	.04	.08	.07	.08
MEANXP	-.08	-.21	.14	.09	.12	.12
XM17	.04	-.05	.10	.11	.11	-.04
XMJADP	.13	.21	-.11	-.03	-.03	-.04

Note that no significant improvement in the ability of the four methods to estimate job ability requirements was obtained. In some cases, mean correlations with the adjusted criterion data were lower than for the unadjusted data.

DISCUSSION

There are a number of possible approaches that one might take in operationalizing the concept of job component validity. The present study used an approach which involved the use of "attibute data" (that is, the ratings of attributes on job elements associated with the Position Aanalysis Questionnaire) as the basis for estimating job ability requirements. Various methods for utilizing the attribute data were employed in the present study. The results of this study indicated, however, that the use of such attribute data probably would have somewhat restricted utility for the job component validity paradigm

Though prediction of the "cognitive" ability requirements was quite respectable, the prediction of the perceptual abilities was only moderate, and the prediction of the psychomotor abilities was very poor. Ther are a number of indications, however, that certain of the findings of this study might be attributed to deficiencies in the specific predictors and criteria used, rather than to the basic approach of using attibute data for the estimation of job ability requirements as they might be used in the job component validity pardigm.

Cumulative vs Critical Behaviors Only Models of Estimation

When using attribute data as the basis for making estimations of the ability requirements of jobs, one might distinguish between two models for combining such data into appropriate estimates. In one case, the ability requirements of jobs are assumed to be influenced by the cumulative importance of a particular ability across all of the various work behaviors (in this case represented by the job elements of the PAQ) which one might find associated with the job. In connection with such a model, some of the behaviors included in such a list would be considered essential to the job while others would be considered to be of only tangential relevance to the job. According to the cumulative model, regardless of the magnitude of the importance of a particular behavior, the ability level needed to perform that behavior would potentially influence the overall level of that ability needed for the job.

On the other hand, one might view ability requirements in terms of the "critical behaviors only" model. Under such a model, the overall ability level required on a specific job would be determined solely by the level of that ability associated with only the most important behaviors which comprise the job. The distinction between the two models of ability requirements seems clear, and the relative effectiveness of the models in estimating job ability requiements across a large sample of jobs was tested as part of the present study.

For the sample of 659 jobs, when considering the prediction of ability requirements across all nine GATB tests, neither model proved to be very effective. The average multiple correlation for the cumulative model methods across all nine GATB tests was .36, while the average multiple correlation for the "critical behaviors only" methods of estimation was .30. This indicates that cumulative methods of estimation offer a slight, though not statistically significant, advantage over the "critical behaviors only" methods in estimating job ability requirements. The fact that those methods using job dimension scores for estimating job requirements were basically cumulative in nature, and that such methods tended to be superior to all other methods of estimating job ability requirements (i.e. those methods which did not involve the use of dimension data), lends further support for the use of cumulative rather than "critical behaviors only" methods. One should note, however, that, by definition, the "critical behaviors only" methods tend to restrict the range of the predictor scores, and thus correlations obtained from the use of these scores might well be lower than they "should" be.

Micro vs Macro Methods of Estimation

The various estimation methods used in this study could also be divided into two distinct groups according to the type of job information upon which they base their estimates of job ability requirements. A number of the methods used "micro" sources of job information in that they based their estimates of the ability requirements of a particular job upon scores derived from the individual PAQ job element ratings obtained for the job, and the individual attribute ratings associated with each of those job elements.

On the other hand, several methods used "macro" sources of job information in which estimates of ability requirements were based upon scores derived from various Q-type and R-type job attribute dimensions. The Q-type dimensions were based upon principal components analyses of the six major divisions of the PAQ, and grouped fairly large numbers of job elements into single categories, i.e. dimensions. The R-type dimensions were based upon R-type principal components analyses of the 49 aptitudinal attributes associated with the PAQ, and grouped these individual attributes into larger ability categories. Due to the grouping of individual job elements and attributes into larger categories, the Q-type and R-type attribute dimensions represent macro sources of job information.

The present study provided strong evidence in favor of the use of methods which utilize macro sources of job information in deriving estimates of job ability requirements. As contrasted with the micro methods of estimation, one might suggest that the effectiveness of such methods for predicting job ability requirements was partially a result of the criteria used in the study. Certain of the GATB tests used as criteria appear to represent "complexes" of abilities rather than single, pure abilities. For example, the test of general intelligence includes subtests concerned with "three dimensional space," "vocabulary," and "arithmetic reason." Similarly, the numerical aptitude test, N, contains both "computation" and "arithmetic reason" subtests. Thus macro methods of estimating job ability requirements might, in certain cases, be better suited for predicting complexes of abilites represented by some of the GATB tests due to the fact that macro methods are based upon broader sources of job information. Micro methods, due to the specific nature of the information involved with these methods, might be less suited as predictors of the more complex GATB tests. The nature of the respective methods might also affect the relative reliability of the two, with the aggregate of information included in the macro methods adding to the reliability of scores based upon such data, thus increasing the correlations associated with macro methods of estimation.

Prediction of the Various Criteria Used in the Study

Three criteria associated with the GATB tests were used in the present study. They were: (1) mean GATB test scores for job incumbents; (2) potential cutoff scores (i.e., for any job, this was the score one standard deviation below the mean test score of job incumbents on each of the GATB tests); (3) the validity coefficients associated with the nine GATB tests for each of the 659 jobs in the sample.

Across all methods of estimating job ability requirements, there were no differences between the prediction of mean GATB test scores and potential cutoff scores for the nine tests. This finding does not nullify, and would perhaps enhance, the suggestion that, for operational purposes, potential cutoff scores are representative of the minimum level of abilities necessary for job performance.

As regards the estimation of ability requirements represented by the criterion of GATB validity coefficients, no method of estimation achieved even a moderate degree of success in making such predictions. This finding was somewhat expected (Mecham, 1970; and Marquardt, 1974). Ghiselli (1959) noted that validity coefficients are characterized by considerable "instability," and thus prediction of such data is extremely difficult.

In Phase II of the study, the mean GATB test scores were "adjusted" so as to hopefully take into account the high degree of intercorrelation among the nine tests of the GATB. In terms of the "adjusted" mean test score criterion, the results of this study were far from encouraging. In no cases were the predictions of the adjusted criterion data higher than those of the unadjusted criterion data. In certain cases the predictions were worse. This finding has two possible implications. One implication is that, since there is no "clean cut" statistical procedure availible for adjusting out the effect of the high mean test score intercorrelations upon the estimation of ability requirements, the procedure used in this study was invalid and was not producing the desired effect upon the problems underlying the data. An alternative to this explanation, and possibly the most reasonable one in the present case, is that the problems associated with the GATB data are so deeply imbedded within the very nature of the data that <u>no</u> statistical procedure would have been able to adjust for these difficulties.

Problems with Predictors

Whenever data are based upon the judgements of humans, one is invariably confronted with the question of the reliability of these data. In terms of the PAQ job element and attribute ratings used in deriving estimates of job ability requiements, two sources of unreliability are possible, i.e. unreliability relating to <u>both</u> the job element ratings and the attribute ratings. If the degree of reliability was low for one or both of these ratings, the use of such data in the present study could well have resulted in the considerable distortion of information concerning the ability requirements of the jobs in the sample. However, evidence has indicated that the reliability relating to the PAQ ratings is quite good. Marquardt (1974) used job dimension scores to estimate the job ability requirements of a large sample of jobs. These dimensions were based upon principal components analyses of the PAQ job elements in each of the six major divisions of the PAQ using as the basis of the analyses the PAQ job analysis ratings for each of the elements across 3700 jobs. Prediction in terms of these job dimension scores was quite good. In the same study, using an attribute data approach to job component validity, Marquardt used attribute dimension scores for 23 dimensions resulting from principal components analyses of the attribute profiles of the elements in each of the six major divisions of the PAQ to estimate job ability requirements. The attribute dimensions were thus based upon attribute ratings associated with the PAQ elements. Prediction in terms of these attribute dimension scores was comparable to that achieved using the job dimension scores based on the job element ratings. It seems, therefore, that while unreliabilty of ratings might have resulted in some reduction in the effectiveness of various methods of estimating job ability requirements, it is not, in itself, sufficient to explain the low correlations found in the present study.

Another possible problem associated with the predictors used in this study can be found in the fact that the methods used by Marquardt (1974) based upon the 23 attribute dimensions resulted in significantly better estimates of the psychomotor abilities than did methods based upon the new 17 attribute dimensions. In the one case, the new 17 dimensions were based upon principal components analyses of the six major PAQ division using job element profiles across 49 "aptitudinal" attributes. Marquardt's 23 attribute dimensions were based upon similar analyses, but used job element profiles across 71 "aptitudinal" <u>and</u> "situational" attributes.

Multiple correlations between Marquardt's attribute dimension scores and the psychomotor GATB mean test scores were in the upper .40's, while the correlations between the attribute dimension scores on the 17 new attribute dimensions and the mean GATB test scores were in the middle .20's. Also, within the present study, the correlations between attribute scores derived using the XMJADP method (based on Marquardt's 23 dimensions) and the mean test scores on the GATB test K ranged as high as .48, while similar correlations using the XM17 method (same process but with the 17 new attribute dimensions) were generally <u>negative</u> in direction. It would appear that the job dimensions based upon both aptitudinal <u>and</u> situational attributes include information which adds significantly to the predictive power of methods based upon these 23 dimensions. The implications of this as regards the criterion data will be discussed later.

Problems with the Criteria

Across all methods of estimation used in the present study, correlations and multiple correlations associated with estimates of the psychomotor job ability requirements were quite low. This is in line with the statements of Trattner, Fine, and Kubis (1955) that the prediction of mental and perceptual aptitudes is generally better than the prediction of aptitudes which are "physical" in nature. Data published by the U.S. Training and Employment Service (Table 15) show that there are moderate intercorrelations among the nine tests of the GATB. Of particular importance to the present study is the fact that the psychomotor tests of the GATB are moderately intercorrelated with the more "cognitive" GATB tests. In view of these intercorrelations, if one were to rank order jobs according to the mean scores of incumbents on the jobs, this ordering would, to some extent, reflect the admixture of the cognitive as well as the psychomotor abilities of the incumbents. This admixture could result in jobs which would normally be expected to rank high (or low) on psychomotor abilities, instead showing less (or more) psychomotor ability levels than would reasonably be expected. Such a ranking would not necessarily reflect an accurate representation of the relative psychomotor ability levels necessary for the jobs.

In the present study, the use of mean GATB scores, rather than individual test scores, has resulted in even higher intercorrelations among the psychomotor and cognitive tests (Table 15). Thus the possible distortion caused by the relationship between the cognitive and psychomotor abilities associated with the jobs in the sample would be even greater than when considering individual test score data. The ranking of jobs according to their relative psychomotor ability levels (as represented by the mean GATB scores) would be expected to present a less than totally accurate picture of the "true" psychomotor ability requirements. Data presented in Appendix L would appear to support this conclusion. Note that many jobs which would normally be expected to be "psychomotor" in nature, e.g. an ironworker, show mean scores lower than those for jobs which are essentially "cognitive" in nature, e.g. a job analyst.

In testing the utility of attribute data in a job component validity paradigm, it is assumed that employees tend to "gravitiate" into those jobs in which they can achieve some relatively successful degree of performance, and that mean GATB test scores of incumbents would thus represent the ability levels necessary for some minimally acceptable degree of job performance. Data in Appendix L would suggest that this is not totally the case for the psychomotor tests.

It seems reasonable to suggest that the intercorrelations found among the psychomotor and cognitive tests are at least partially responsible for the apparent inconsistencies in the ranking of the jobs according to the mean psychomotor test scores of incumbents on the jobs. It may also be that a more "basic" factor underlies the apparent inconsistencies in the rankings. It may be that for some of the jobs which are predominantly manual in nature, the psychomotor abilities necessary for performance are of relatively minor importnance in determining the overall "success" of the persons on those jobs. Most workers might possess the minimum ability level which would enable the workers to adequately perform the job in question. In this case, the degree to which the person is "successful" on the job (an would thus have gravitiated into that particular position) would depend upon several factors in addition to the psychomotor abilities he possesses. If this were so, one could not expect any simple ranking of jobs according to the mean test scores of incumbents to represent the ability levels needed for successful performance. Successful performance would, instead, be determined by an admixture of the psychomotor, cognitive, situational, and personality factors involved in the job.

Marquardt (1974) used attribute dimensions based upon both aptitudinal and situational attributes to predict job ability requirements. Predictions using these dimensions were generally better than the predictions associated with dimensions based solely aptitudinal attributes used in the present study. The differences between predictions based upon Marquardt's attribute dimensions as opposed to the predictions based upon the new attribute dimensions used in the present study were minimal for the cognitive abilities. The difference between the predictive power of the two sets of dimensions was somewhat greater for the perceptual abilities, and was greatest for the psychomotor abilties.

Although the stituational attributes used in forming Marquardt's dimensions are described in terms of various "work situations," they are assumed to reflect thos interest, personality, and temperment factors which enable the incumbents on a job to "adapt" to the specified work situations. It would thus appear that the inclusion of such non-aptitudinal information into the prediction system generally increases the level of prediction possible. These results would suggest that success on jobs which are dominantly psychomotor in nature may be more dependent upon "adaptibility" factors (such as interest, personality, or temperment) than on psychomotor abilities.

CONCLUSION

In the present study an approach was taken to the concept of job component validity which utilized the attribute rating data associated with the Position Analysis Questionnaire as the basis for estimating job ability requirements. Within this general "attribute approach," a number of different models of estimation were compared as to their relative effectiveness in predicting job ability requirements. The models used included "micro" models, "macro" models, "cumulative" models, and "critical behaviors only" models.

The results of the present study indicated that "macro" models of estimation are more effective in estimating job ability requirements than are "micro" models. However, in the case of such macro models, "good" estimation of ability requirements was possible only when the macro sources of job information used in such methods were based upon large numbers of diverse human attributes (Marquardt, 1974).

It was also shown that "cumulative" methods of estimating job ability requirements were only slightly better than the "critical behaviors only" methods. This slight advantage was based primarily upon the fact that macro methods of estimation, which did relatively well in estimating job ability requirements, were of a cumulative nature.

When viewed as a whole, however, the approach to job component validity taken in the present study, i.e. the use of PAQ attribute data, was differentially effective in estimating job ability requirements. Though prediction of cognitive abilties was relatively good, the prediction of perceptual abilities was only moderate, and the prediction of psychomotor abilities was very poor. When data from the present study were compared to previous work using the job component validity paradigm (Marquardt, 1974), it was apparent that the approach taken in the present study which used attribute data for estimating job ability requirements was generally less effective than the approach taken by Marquardt which involved the use of PAQ job analysis rating data as the basis for the estimation of ability requirements for jobs. It would appear at least that for the present time the optimum approach for the application of the concept of job component validity should be based upon job dimension data derived from PAQ job analysis ratings.

The results of the present study probably should not be taken as to preclude any future investigation of the attribute data approach to the concept of job component validity. In terms of any further exploration of the potential utility of attribute data for estimating job ability requirements, it would appear that attribute dimensions resulting from principal components analyses of job element profiles across large numbers of diverse human attributes would have the best possible chance of providing adequate estimates of ability levels for use in establishing jbo component validity.

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APPENDIX A

Methods, Models, Abbreviations, and Descriptions Associated With the 21 Methods of Estimating Job Ability Requirements Used in This Study

Method	Models: --Cumulative	--Critical Behaviors	--Macro	--Micro	Abbreviation	Description
1	X			X	SUMXP	Sum of the cross-products for each attribute computed from the FULLXP matrix
2	X			X	MEANXP	Mean of the cross-products for each attribute computed from the FULLXP matrix
3	X			X	ABOVE	The number of cross-products computed for each attribute from the FULLXP matrix which fell above the grand mean
4	X			X	BELOW	The number of cross-products computed for each attribute which fell below the grans mean
5	X			X	ABOBEL	The ratio of ABOVE/BELOW
6a	X			X	PCT2	The % of cross-products computed for each attribute for the FULLXP matrix which fell into Quintile 2
6b	X			X	PCT3	The % of cross-products computed for each attribute for the FULLXP matrix which fell into Quintile 3
6c	X			X	PCT4	The % of cross-products computed for each attribute which fell into Quintile 4
6d	X			X	PCT5	The % of cross-products computed for each attribute which fell into Quintile 5
7		X		X	SUM5	The sum of the cross-products computed for each attribute from the FULLXP matrix for those element-attribute pairings where the job element rating= 5.0

APPENDIX A (Cont.)

Method	Models: --Cumulative	--Critical Behaviors	--Macro	--Micro	Abbreviation	Description
8		X		X	MEAN5	The mean of the cross-products computed for each attribute from the FULLXP matrix for those element-attribute pairings where the PAQ job element rating= 5.0
9		X		X	R1SUM	The sum of the cross-products computed for each attribute for the R1XP matrix
10		X		X	R1MEAN	The mean of the cross-products computed for each attribute for the R1XP matrix
11		X		X	R2SUM	The sum of the cross-products computed for each attribute for the R2XP matrix
12		X		X	R2MEAN	The mean of the cross-products computed for each attribute for the R2XP matrix
13		X		X	R2NUM	The number of cross-products computed for each attribute for the R2XP matrix
14a			X		XMJADP	Job attribute profiles developed using the 23 Marquardt attribute dimensions
14b			X		XM17	Job attribute profiles developed using the 17 new attribute dimensions
15			X		NEM17	Job attribute dimension scores for the 17 new attribute dimensions
16			X		SADAP	Dimension scores for the 7 R-type dimensions
17			X		RADAP	Job attribute dimensions values resulting from a combination of data from both the seven R-type attribute dimensions and the 17 Q-type attribute dimensions

APPENDIX B

Principal Components Resulting from Analyses of the Six Major Divisions of the PAQ

Components resulting from the analysis of PAQ job elements: division 1, information input. A Q-type principal componenets analysis was carried out using the job elements in the Information Input division of the PAQ (job elements 1-35). This analysis yielded a total of three principal components accounting for 69.4% of the total variance. The interpretations associated with these three dimensions are given below.

(1) Division 1, factor 1: visual perception/interpretaion---this dimension accounted for 47.1% of the total variance. It is a relatively broad dimension characterized by job activities which involve the perception and/or interpretation of visual input from the job.

(2) Division 1, factor 2: non-visual perception/interpretation---this dimension acccounted for 13.5% of the total variance. It is characterized primarily by job activities which involve the use of non-visual sources of job information, e.g. feeling, tasting, smelling, or hearing.

(3) Division 1, factor 3: body movement sensing/ balance---this dimension accounted for 8.8% of the total variance. Three job elements received substantial loadings on this dimension. They are characterized primarily by the degree to which the sensing of physical movement, position or balance, such as is necessary in the use of mechanical devices, are needed for job performance.

Components resulting from the analysis of PAQ job elements: division 2, mental processes. A Q-type principal components analysis was carried out using the job elements from the Mental Processes division of the PAQ (job elements 36-49). This analysis resulted in a

APPENDIX B (Cont.)

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total of two principal components accounting for 85.0% of the total variance. The interpretations associated with these dimensions are given below.

(1) Division 2, factor 1: reasoning, decision making, and related mediation activities---this dimension accounted for 45.9% of the total variance. It is a rather broad dimension which involves activities which depend upon reasoning, decision making or similar types of mediation processes, and which necessitate the acquisition of such mediation "skills" through experience, education, or training.

(2) Division 2, factor 2: integrating information---this dimension accounted for 39.1% of the total variance. Job activities included in this dimension are those which involve the collection and integration of information obtained from the job.

Components resulting from the analysis of PAQ job elements: division 3, work output. A Q-type principal components analysis was carried out using the job elements from the Work Output division of the PAQ (job elements 50-98). This analysis yielded a total of three principal componenets acccounting for 84.5% of the total variance. The interpretations associated with these dimensions are given below.

(1) Division 3, factor 1: manual manipulation/control---this dimensions accouted for 33.9% of the total variance. It is a broad dimension including a large number of PAQ job elements. It is characterized primarily by job elements which involve some form of manipulation and/or the control of various materials/devices associated with the job.

(2) Division 3, factor 2: handling/general-body activities---this dimension accounted for 25.0% of the total variance. It is characterized by activities which involve general body movement and/or the physical handling or manipulation of various types of materials/devices.

APPENDIX B (Cont.)

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(3) Division 3, factor 3: varied physical/controlling activities--- this dimension accounted for 25.6% of the total variance. It is a rather broad dimension including a large number of PAQ job elements. It is characterized primarily by job activities which involve a variety of physical activities in the operation or control of equipment and/or the handling or use of materials or devices associated with the job.

Components resulting from the analysis of PAQ job elements: division 4, relationships with other persons. A Q-type principal components analysis was carried out using the job elements in the Relationships with Other Persons division of the PAQ (job elements 99-134). This analysis yielded a total of two principal components accounting for 85.0% of the total variance. The interpretations associated with these dimensions are given below.

(1) Division 4, factor 1: interpersonal communication--- this dimension accounted for 71.5% of the total variance. It is a very broad dimension with significant loadings on a large number of PAQ job elements. It is characterized primarily by job activities which involve interpersonal communications carried out for different purposes and with different types of people.

(2) Division 4, factor 2: unnamed---this dimension accounted for 13.5% of the total variance. Some of the dominant job elements in this dimension seem not to be logically related to one another, and thus, no interpretation of this dimension was made.

Components resulting from the analysis of PAQ job elements: division 5, job context. A Q-type principal components analysis was carrried out using the PAQ job elements in the Job Context division of the PAQ (job elements 135-153). This analysis yielded

APPENDIX B (Cont.)

total of three principal components accounting for 71.6% of the total variance. The interpretations associated with these dimensions are given below.

(1) Division 5, factor 1: personally demanding situations---this dimension accounted for 29.0% of the total variance. It is characterized by job situations which are largely interpersonal in nature, and which are typically viewed as being demanding and/or frustrating for the individual.

(2) Division 5, factor 2: unpleasant physical environment---this dimension accounted for 21.7% of the total variance. It is characterized by situations which are generally considered unpleasant in nature.

(3) Division 5, factor 3: hazardous physical environment---this dimension accounted for 20.9% of the total variance. It is characterized by jobs which are generally considered to be hazardous in nature.

Components resulting from the analysis of PAQ job elements: division 6, other job characteristics. A Q-type principal components analysis was carried out using the job elements from the Other Job Characteristics division of the PAQ (job elements 154-182). This analysis yielded a total of four principal components accounting for 73.6% of the total variance. The interpretations associated with these dimensions are given below.

(1) Division 6, factor 1: schedule/work attire--this dimension is probably without real meaning since the median ratings across almost all of the 49 attributes are "0" (of no relevance) for the job elements in this dimension. The dimension accounted for 28.8% of the total variance. These job elements which received substantial loadings on this dimension are characterized by the work schedules or amount of time the incumbent spends on the job or the type of attire he must wear.

APPENDIX B (Cont.)

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(2) Division 6, factor 2: routine/repetitive work activities---this dimension accounted for 16.3% of the total variance. It is characterized primarily by job situations in which work procedures are clearly specified and activities tend to be routine and/or repetitive in nature.

(3) Division 6, factor 3: job responsibility---this dimension accounted for 16.2% of the total variance. It is characterized primarily by job elements which reflect the level of responsibility for various duties/aspects of the job.

(4) Division 6, factor 4: attentive/discriminating work demands---this dimension accounted for 12.4% of the total variance. It is characterized primarily by job situations which involve vigilance or attentiveness, or in which the job incumbent must be attentive to detail or be alert to various stimuli in the work environment.

APPENDIX C

Job Element Dimensions Based on Component Analysis of Job Element Attribute Profiles: PAQ Division 1, Information Input

Attribute Dimension and Job Elements with Loadings of .45 or Above		Rotated Loading
Factor 1: Visual perception/interpretation		
32	Inspecting	.91
3	Pictorial materials	.90
11	Man-made environment	.88
8	Materials in process	.88
22	Depth perception	.87
34	Estimating size	.87
5	Visual displays	.86
10	Features in nature	.86
33	Estimating quantity	.84
20	Near visual differentiation	.83
23	Color perception	.81
9	Materials not in process	.81
2	Quantitative materials	.80
4	Pattern/related devices	.79
21	Far visual differentiation	.79
30	Estimating speed-process	.79
14	Art or decor	.79
31	Judging condition/quality	.79
29	Estimating speed-moving objects	.77
13	Events or circumstances	.75
7	Mechanical devices	.75
28	Estimating speed-moving parts	.70
6	Measuring devices	.66
12	Behavior	.66
1	Written materials	.63
35	Estimating time	.49

APPENDIX C (Cont.)

Attribute Dimension and Job Elements with Loadings of .45 or Above		Rotated Loading
Factor 2: Non-visual perception/interpretation		
24	Sound pattern recognition	.86
16	Non-verbal sounds	.85
25	Sound differentiation	.82
15	Verbal sources	.72
18	Odor	.64
19	Taste	.61
35	Estimating time	.47
17	Touch	.45
Factor 3: Body movement sensing/balance		
26	Body movement	-.86
27	Body balance	-.75
7	Mechanical devices	-.46

APPENDIX D

Job Element Dimensions Based on Component Analysis of Job Element Attribute Profiles: PAQ Division 2, Mental Processes

Attribute Dimension and Job Elements with Loadings of .45 or Above		Rotated Loading
Factor 1: Reasoning, decision making and related mediation processes		
46	Job-related knowledge	.87
47	Training	.85
37	Reasoning in problem solving	.84
36	Decision making	.82
45	Education	.80
38	Amount of planning/scheduling	.75
44	Short term memory	.72
40	Analyzing information	.64
39	Combining information	.62
48	Using mathematics	.57
Factor 2: Integrating information		
43	Transcribing	.91
42	Coding/decoding	.91
41	Compiling	.83
39	Combining information	.74
40	Analyzing information	.73
48	Using mathematics	.70
38	Amount of planning/scheduling	.50
45	Education	.48
36	Decision making	.48
37	Reasoning in problem solving	.48
44	Short-term memory	.45

APPENDIX E

Job Element Dimensions Based on Component Analysis of Job Element Attribute Profiles: PAQ Division 3, Work Output

Attribute Dimension and Job Elements with Loadings of .45 or Above		Rotated Loading
Factor 1: Manual manipulation/control		
57	Measuring devices	.91
55	Drawing/related devices	.88
49	Man powered precision tools	.86
91	Finger manipulation	.86
79	Assembling/disassembling	.84
58	Technical-related devices	.83
76	Setting up/adjusting	.80
77	Manually modifying	.80
53	Powered precision tools	.79
56	Applicators	.78
92	Hand-arm manipulation	.75
93	Hand-arm steadiness	.75
63	Keyboard devices	.74
62	Variable setting controls	.74
50	Man-powered non-precision tools	.67
78	Material controlling	.66
59	Machines/equipment	.65
64	Frequent adjusting hand controls	.63
66	Continuous hand controls	.62
94	Eye/hand-foot coordination	.61
80	Arranging/positioning	.61
54	Powered non-precision tools	.61
52	Handling-devices/tools	.60
95	Limb movement without visual contact	.60
81	Feeding/off bearing	.59

APPENDIX E (Cont.)

Attribute Dimension and Job Elements with Loadings of .45 or Above		Rotated Loading
Factor 1 (cont.)		
82	Physical handling	.58
60	Activation controls	.55
61	Fixed setting controls	.53
51	Long handle tools	.52
96	Hand-ear coordination	.46
Factor 2: Handling/general-body activities		
85	Level of physical exertion	.92
87	Standing	.87
84	Balancing	.86
88	Walking/running	.85
83	Highly skilled body coordination	.83
89	Climbing	.82
90	Kneeling/stooping	.79
86	Sitting	.71
51	Long handled tools	.67
82	Physical handling	.62
52	Handling devices/tools	.62
50	Man-powered precision tools	.57
81	Feeding/off bearing	.54
68	Man powered vehicles	.54
73	Man-moved mobile equipment	.54
80	Arranging/positioning	.53
95	Limb movement without visual contact	.52
93	Hand-arm steadiness	.52
92	Hand-arm manipulation	.50

APPENDIX E (Cont.)

Attribute Dimension and Job Elements with Loadings of .45 or Above		Rotated Loading
Factor 2 (cont.)		
77	Manually modifying	.48
94	Eye/hand-foot coordination	.48
60	Activation controls	.46
Factor 3: Varied physical/controlling activities		
71	Powered water vehicles	.84
69	Powered highway/rail vehicles	.84
72	Air/space vehicles	.84
75	Remote controlled equipment	.83
74	Operating equipment	.82
70	Powered mobile equipment	.80
67	Continuous foot control	.71
68	Non-powered vehicles	.71
65	Frequently adjusted foot controls	.71
73	Man-moved mobile equipment	.70
61	Fixed setting controls	.66
60	Activation controls	.62
64	Frequently adjusted hand controls	.60
66	Continuous hand controls	.59
59	Machines/equipment	.58
54	Powered non-precision tools	.57
78	Material controlling	.55
93	Hand-arm steadiness	.52
62	Variable setting controls	.52
81	Feeding/off bearing	.50
53	Powered precision tools	.50

APPENDIX F

Job Element Dimensions Based on Component Analysis of Job Element Attribute Profiles: PAQ Division 4, Relationships with Other Presons

Attribute Dimension and Job Elements with Loadings of .45 or Above		Rotated Loading
Factor 1: Interpersonal communication		
126	Direction/supervising personnel	.97
99	Persuading	.97
97	Advising	.97
98	Negotiating	.97
130	Staff functions	.97
100	Instructing	.96
114	Professional personnel	.95
111	Executives/officials	.95
103	Non-routine information exchange	.94
101	Interviewing	.94
112	Middle management/staff	.93
129	Coordinates activities	.93
123	Clients/patients/counselees	.91
125	Supervision/non-supervisory personnel	.91
119	Buyers	.91
104	Public speaking	.90
131	Supervision received	.90
122	Students/trainees/apprentices	.90
124	Special talent groups	.90
128	Supervises non-employees	.90
127	Number of persons for whom responsible	.89
113	Supervisors	.89
115	Semi-professional personnel	.88
120	Public customers	.87

APPENDIX F (Cont.)

Attribute Dimension and Job Elements with Loadings of .45 or Above		Rotated Loading
Factor 1 (cont.)		
118	Sales personnel	.87
121	The public	.86
110	Entertaining	.84
102	Routine information exchange	.77
116	Clerical personnel	.76
105	Writing	.75
117	Manual and service workers	.61
Factor 2: Unnamed		
106	Signaling	-.79
109	Serving/catering	-.78
107	Code communications	-.66
108	Entertaining	-.61
116	Clerical personnel	-.57
117	Manual and service workers	-.48

APPENDIX G

Job Element Dimensions Based on Component Analysis of Job Element Attribute Profiles: PAQ Division 5, Job Context

Attribute Dimension and Job Elements with Loadings of .45 or Above		Rotated Loading
Factor 1: Personally demanding situations		
145	Civic obligations	
147	Strained personal contacts	.95
150	Non-job required social contacts	.94
148	Personal sacrifice	.93
146	Frustrating situations	.92
149	Interpersonal conflict situations	.89
Factor 2: Unpleasant physical environment		
133	High temperature	.91
134	Low temperature	.86
138	Dirty environment	.78
139	Awkward or confing space	.77
136	Vibration	.67
132	Out-of-door environment	.67
135	Air contamination	.48
Factor 3: Hazardous physical environment		
143	Permanent partial impairment	.97
142	Temporary disability	.96
144	Permanent total disability of impairment	.96
141	First aid cases	.91

APPENDIX H

Job Element Dimensions Based on Component Analysis of Job Element Attribute Profiles: PAQ Division 6, Other Job Characteristics

Attribute Dimension and Job Elements with Loadings of .45 or Above		Rotated Loading
Factor 1: Schedule/work attire		
161	Irregular hours	.91
164	Typical day and night hours	.86
152	Specific uniform/apparel	.85
160	Variable shift work	.83
162	Typical day hours	.83
163	Typical night hours	.83
158	Irregular work	.81
159	Regular work	.79
177	Travel	.79
155	Informal attire	.79
151	Business suit or dress	.75
156	Apparel style optional	.72
153	Work clothing	.53
Factor 2: Routine/repetitive work activities		
166	Repetitive activities	.86
165	Specific work place	.84
167	Cycled work activities	.80
168	Following set procedures	.73
153	Work clothing	.60
170	Precision	.58
169	Time pressure of situation	.56

APPENDIX H (Cont.)

Attribute Dimension and Job Elements with Loadings of .45 or Above		Rotated Loading
Factor 2 (cont.)		
159	Regular work	.52
157	Regular hours	.46
Factor 3: Job responsibility		
180	General responsibility	-.91
182	Criticality of position	-.90
176	Up-dating job knowledge	-.86
181	Job structure	-.85
179	Responsibility-material assets	-.82
175	Working under distractions	-.61
178	Responsibility-safety	-.47
Factor 4: Attentive/discriminating work demands		
173	Vigilance-infrequent events	.95
174	Vigilance-continually changing events	.91
172	Recognition	.87
171	Attention to detail	.72
178	Responsibility-safety	.55

APPENDIX I

List of Twenty PAQ Attributes Which Closely Match GATB Test Data

---

Cognitive attributes:

- Verbal comprehension
- Word fluency
- Oral commmunication
- Numerical computation
- Arithmetic reasoning
- Convergent thinking
- Divergent thinking
- Intelligence

Perceptual attributes:

- Visual form perception
- Perceptual speed
- Closure
- Spatial visualization
- Near visual acuity
- Far visual acuity

Psychomotor attributes:

- Finger dexterity
- Manual dexterity
- Arm/hand positioning
- Eye/hand coordination
- Response integration
- Speed of limb movement

APPENDIX J

PAQ Attributes Used as Predictors of Mean Test Scores on Each of the Nine GATB Tests

---

Test G, general intelligence:

- Verbal comprehension
- Arithmetic reasoning
- Convergent thinking
- Divergent thinking
- Intelligence
- Spatial orientation

Test V, verbal ability:

- Verbal comprehension
- Word fluency
- Oral communication

Test N, numerical ability:

- Numerical commutation
- Arithmetic reasoning

Test S, spatial ability:

- Visual form perception
- Closure
- Spatial visualization

Test P, form perception:

- Visual form perception
- Perceptual speed
- Closure

APPENDIX J (Cont.)

Test P, form perception (cont.):

Spatial visualization
Near visual acuity
Far visual acuity

Test Q, clerical perception:

Verbal comprehension
Convergent thinking
Perceptual speed
Near visual acuity

Test K, motor coordination:

Finger dexterity
Manual dexterity
Arm/hand positioning
Eye/hand coordination
Response integration
Speed of limb movement

Test F, finger dexterity:

Finger dexterity
Manual dexterity
Arm/hand positioning
Response integration

APPENDIX J (Cont.)

Test M, manual dexterity:

- Finger dexterity
- Manual dexterity
- Arm/hand positioning
- Eye/hand coordination
- Response integration

APPENDIX K

Population and Sample Regression Equations for Adjusting the Criterion of Mean Test Scores

---

Population equations:

$G= .45V+.42N+.33S-.03P-.01Q-.03K-.01F+.01M$

$V=1.39G-.46N-.39S+.01P+.14Q+.07K+.01F-.05M$

$N=1.45G-.50V-.41S+.08P+.14Q+.06K-.001F-.01M$

$S=1.81G-.69V-.66N+.25P-.06Q-.02K+.05F-.01M$

$P=-.24G+.04V+.22N+.41S+.41Q+.08K+.10F+.08M$

$Q=-.09G+.31V+.28N-.08S+.32P+.15K\_.04F-.02M$

$K=-.34G+.29V+.22N-.04S+.11P+.26K+.07F+.27M$

$F=-.13G+.04V-.01N+.15S+.17P+.10Q+.09K+.37M$

$M= .20G-.27V-.58N-.03S+.16P-.06Q+.38K+.39F$

Sample equations:

$G= .53V+.43N+.32S+.06P-.05Q-.14K-.003F+.002M$

$V=1.40G-.51N-.35S-.24P+.21Q+.29L+.01F-.02M$

$N=1.79G-.80V-.50S-.06P+.10Q+.23K+.003F+.003M$

$S=1.89G-.78V-.72N+.27P-.14Q+.12K-.02F+.01M$

$P= .48G-.73V-.11N+.37S+.57Q+.27K+.08F-.01M$

$Q=-.53G+.80V+.25N-.25S+.72P+.15K-.05F+.01M$

$K=-1.26G+1.olV=.51N+.19S+.30P+.13Q+.02F+.06M$

$F=-.56G+.94V+.13N-.48S+1.74P-.86Q+.41K+.35M$

$M= .52G-2.00V+.19N+.51S-.31P=.20Q+.15K+.50F$

APPENDIX L

A Subsample of Jobs in the Sample Sorted
in Descending Order According to the Mean Scores
on the GATB Motor Coordination Test, K

Job Name	Mean Score
Biologist	125
Scientific programmer	119
Programmer analyst	119
Pharmacist	119
Personnel interviewer	117
Tool clerk	117
Life insurance compensation analyst	117
Job analyst	116
Salary administration analyst	116
State school caseworker	115
Computer operator	114
Clerk-stenographer	113
Statistical typist	113
Electrical project engineer	113
Accountant	112
Auditor	112
Industrial artist	111
Supermarket cashier	110
Police patrolman	109
Keypunch operator	108
Telephone operator	106
Punch press operator	95
Plumber	92
Ironworker	86

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