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ABSTRACT

Recent developments in dichotomous factor analysis based on multidimensional item response models (Bock and Aitkin, 1981; Muthen, 1978) provide an effective method for exploring the dimensionality of questionnaire items. Implemented in the TESTFACT program, this "full information" item factor analysis accounts not only for the pairwise joint frequencies of correct/incorrect responses, but also for additional information in higher order joint frequencies in the sample of dichotomously scored items. This paper illustrates this method's utility by analyzing a questionnaire on affective outcomes of schooling using the expected a posteriori (EAP) method of estimating ability scores. The 40 item questionnaire with four subscales (Punctuality, Honesty, Cooperation, and Curiosity) was developed to measure a set of potential outcomes of schooling's "latent curriculum". A stepwise full-information item factor analysis was performed on data from 700 elementary school students which identified three factors: interpersonal relations, active participation, and studious attitude. The advantages of using EAP scores over the use of raw scores to simplify the interpretation of multivariate analysis of variance where there are fewer concepts to discuss are illustrated. The full information factor analysis is strongly recommended for construct validation in the initial preparation stage of item construction for psychological measuremnt. (BS)

AFFECTIVE OUTCOMES OF SCHOOLING: FULL-INFORMATION ITEM FACTOR ANALYSIS OF A STUDENT QUESTIONNAIRE

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Recent developments in dichotomous factor analysis based on multidimensional item response models (Bock and Aitkin, 1981; Muthen, 1978) provide an effective method for exploring the dimensionality of questionnaire items. The purpose of this paper is to illustrate the utility of this method for item factor analysis in three sets of data. The first two sets are simulated, and the third set is an analysis of a questionnaire on affective outcomes of schooling (Engelhard, 1985).

Description of the Item Factor Analysis Model

In adapting Thurstone's multiple factor model to dichotomous data, Bock and Aitkin (1981) consider the response process, y_{ij}, of subject i and item j to be a linear combination of m normally distributed latent variables, θ, weighted by the factor loadings, α ; that is,

$$y_{ij} = \alpha_{j1}\theta_{1i} + \alpha_{j2}\theta_{2i} + \dots + \alpha_{jm}\theta_{mi} + \upsilon_j\delta_j \qquad (1)$$

For a randomly sampled subject, it is assumed that $\underline{\theta}$, $\underline{y}$ and $\underline{\delta}$ are multivariate normal:

$$\underline{\theta} \sim N(\underline{0}, I) \qquad (2)$$

$$\underline{y} \sim N(\underline{0}, I) \qquad (3)$$

$$\underline{\delta} \sim N(\underline{0}, D_\sigma) \qquad (4)$$

Assumptions (2) and (3) imply that the diagonal elements of D_σ in (4), denoted as σ_j^2, are

$$\sigma_j^2 = 1 - \sum_{k=1}^{m} \alpha_{jk}^2 \tag{5}$$

The classical factor analysis model for continous variables assumes that the response process is directly observable. In contrast to this model, the factor analysis model for categorical variables assumes that the response process y_{ij} is latent and realized only as a vector of dichotomous response variables, $\underline{x}_i' = (x_{i1}, x_{i2}, \ldots x_{in})$ according to the following psychological mechanism:

$$x_{ij} = \begin{cases} 1 \text{ if } y_{ij} \geq \gamma_j \\ 0 \text{ if } y_{ij} < \gamma_j \end{cases},$$

where γ_j is a threshold parameter associated with item j. Therefore, the probability of a positive response by subject i to item j, given the subject's m-dimensional latent ability, $\underline{\theta}_i$, is

$$P(x_{ij}=1 \mid \underline{\theta}_i)$$

$$= \frac{1}{\sqrt{2\pi}\sigma_j} \int_{\gamma_j}^{\infty} \exp\left[-\frac{1}{2}\left(\frac{y_{ij} - \Sigma\alpha_{jk}\theta_{ki}}{\sigma_j}\right)^2\right] dy_{ij} \tag{6}$$

Introducing the change in the variable,

$$t = (y_{ij} - \Sigma\alpha_{jk}\theta_{ki})/\sigma_j \quad ,$$

we have

$$dy_{ij} = \sigma_j dt$$

and, when

$$y_{ij} = \gamma_j$$

$$t = (\gamma_j - \Sigma\alpha_{jk}\theta_{ki})/\sigma_j \quad ,$$

the model (6) can then be rewritten with slope parameters a_{jk} and location parameters c_k as follows:

$$P(x_{ij}=1 \mid \underline{\theta}_i)$$

$$= \int_{-(\Sigma a_{jk}\theta_{ki} + c_j)}^{\infty} \phi(t)\, dt$$

$$= \Phi_j(\underline{\theta}_i) \tag{7}$$

where

$$a_{jk} = \alpha_{jk}/\sigma_j \tag{8}$$

and

$$c_j = - \gamma_j / \sigma_j \tag{9}$$

From (5), (8) and (9), we obtain the following formulas to convert the slope and location estimates to factor loadings and threshold values:

$$\alpha_{jk} = a_{jk} / d_j \tag{10}$$

and

$$\gamma_j = - c_j / d_j \tag{11}$$

where

$$d_j^2 = (1 + \Sigma a_{jk}^2) \tag{12}$$

A guessing or lower asymptote parameter g_j, can also be incorporated in model (7) as follows:

$$\Phi_j^*(\underline{\theta}_i) = g_j + (1-g_j)\, \Phi_j(\underline{\theta}_i) \tag{13}$$

The iterative procedure developed by Bock and Aitkin (1981) for obtaining the parameters in the multidimensional item response model (7) is based on marginal maximum likelihood estimation, and the EM algorithm of Dempster, Laird and Rubin (1977). Since this approach to item factor analysis accounts not only for the pairwise joint frequencies of correct/incorrect responses, but also for additional information in higher order joint frequencies in the sample of dichtomously scored items, it is called "full-information" item factor analysis.

This method is implemented in the TESTFACT program of Wilson, Wood and Gibbons (1984). At each step of the analysis, the solution from a principal factor analysis for the current number of factors provides initial estimates of the parameters. After the final estimation cycle is completed, estimated values are listed in the form of factor loadings and thresholds, as well as a set of slope and intercept parameter estimates. The TESTFACT program provides the option for conducting a stepwise analysis. The chi-square fit statistics for each solution and the reduction from the previous solution provide a large sample test of significance of factors added to the model. The factor loadings from the full-information solution are rotated orthogonally to the varimax criterion and then obliquely to the promax criterion, at the option of the user. Because the computation of the full-information factor solution increases exponentially in the number of factors, the present version of the TESTFACT program is limited to a maximum of five factors.

The Expected A Posteriori Estimator

Bock and Aitkin (1981) present three methods of estimating ability scores; the maximum likelihood estimator (MLE), the maximum a posteriori (MAP) estimator, and the expected a posteriori (EAP) estimator. We discuss below some reasons for preferring the EAP estimator. The EAP estimator for a response pattern is given by

$$\tilde{\theta}_{ik} = E(\theta_{ik} \mid \underline{x}_i)$$

$$= \frac{\int_{\underline{\theta}} \theta_k g(\underline{\theta}) \prod_{j=1}^{n} \Phi_j^{x_{ij}}(\underline{\theta}) \left[1-\Phi_j(\underline{\theta}) \right]^{1-x_{ij}} d\underline{\theta}}{\int_{\underline{\theta}} g(\underline{\theta}) \prod_{j=1}^{n} \Phi_j^{x_{ij}}(\underline{\theta}) \left[1-\Phi_j(\underline{\theta}) \right]^{1-x_{ij}} d\underline{\theta}} \quad (14)$$

In the TESTFACT program, (14) is evaluated numerically by m-fold Gauss-Hermite product quadrature using the nodes and weights for one-dimensional quadrature (Stroud and Sechrest, 1966).

The EAP estimator is known to be biased when the number of items is finite. However, unlike the MLE, the EAP scores can be computed for response patterns with all correct and all incorrect responses. Furthermore, the EAP estimators can be used with a discrete prior in place of $g(\theta)$, which is not possible for the MAP estimator. In order to illustrate the advantage of the EAP scores, we have conducted two simulation studies.

For the first study, we generated 200 pairs of independently and identically distributed random variables, $\underline{\theta} \sim N(\underline{0},I)$. The two dimensional item parameter estimates of the Auto and Shop Information Test in the ASVAB obtained by Mislevy and Bock (1984) were used to generate the simulated dichotomous item responses to 25 items. Assuming the guessing parameter to be constant, we recalibrated the item statistics for the normal ogive item response model (13). The two dimensional varimax factor loadings were computed from these item parameter estimates. The EAP scores in the two dimensional continuum, which are denoted, $\tilde{\theta}_1$ and $\tilde{\theta}_2$, were computed from the item parameter estimates after the varimax rotation. Twenty Gauss-Hermite quadrature points and weights in each dimension were used for the numerical integration.

Multivariate multiple regression analysis of the generated random variables θ on the EAP estimates $\tilde{\theta}$ was performed. No significant cubic term was detected. The regression function is

$$\begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix} = \begin{bmatrix} 0.012 \\ 0.006 \end{bmatrix} + \begin{bmatrix} 0.954 & -0.029 \\ 0.036 & 1.019 \end{bmatrix} \begin{bmatrix} \tilde{\theta}_1 \\ \tilde{\theta}_2 \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix}$$

$$= \begin{bmatrix} \hat{\tau}_1 + \varepsilon_1 \\ \hat{\tau}_2 + \varepsilon_2 \end{bmatrix}$$

The actual values of the EAP scores depend upon the particular choice of rotation. Nevertheless, the major and minor diagonal of the regression coefficient matrix became close to 1 or 0 respectively. In other words, the EAP scores based on the varimax solution are essentially uncorrelated. This is not true of other methods of computing factor scores (Harman , 1976).

Plots of θ's and τ's in the first and second dimensions are presented in Figures 1 and 2 respectively. There are noticeable ceiling effects in Figure 1. Since each EAP score is computed based on its corresponding response pattern, the ceiling effect or floor effect in the EAP estimates is expected to vanish if additional items are added to a test or extremely difficult or easy items are removed from a certain length test. The coefficients of multiple determination, R^2, are 0.4513 in Figure 1 and 0.6054 in Figure 2. When the same simulation procedure described above was repeated with 500 cases, the R^2 dropped to 0.4147 and 0.5660 respectively. This may be largely due to the poor convergence of item parameter estimation with relatively small sample size. Small sample size becomes problematic in computing the EAP scores only when the item parameters must be estimated from the same observed responses. Otherwise, increasing the length of the test leads to more reliable EAP scores.

INSERT FIGURES 1 AND 2 ABOUT HERE

For the second simulation study, we split a set of 30 unidimensional item estimates of the ASVAB Arithmetic test (Mislevy and Bock, 1984) into 15 odd-number items and 15 even-number items. The 1000 dichotomous item response vectors for each set of 30 items were generated ~~based~~ on the guessing model and the same underlying unidimensional ability distribution. This experiment closely simulates the situation in which the same group of students takes two parallel forms of a test in a certain time interval. The MLE and the EAP estimates were computed from these sets of even-number and odd-number items, and they are plotted in Figure 3 and 4 respectively.

INSERT FIGURES 3 AND 4 ABOUT HERE

Since guessing effects are included in the item response model, the ceiling effects appear in both plots. In addition to the ceiling effects, the plot of the MLE shows that the ability scores are more dispersed at the lower end of the continuum. This is because we cannot obtain the MLE for extreme scores. The unreliablity of the MLE scores at the lower and higher ends of the ability scale may be accentuated when the length of a test is not very long or highly heterogenous guessing effects are found. The comparison between the MLE and the EAP estimates reveals, therefore, that the EAP estimates are a more reliable measure than the MLE. This nature of the EAP scores is important since parallel forms are frequently required in educational testing.

The Full-Information Item Factor Analysis of the School Affect Data

The affective outcomes of schooling questionnaire that is analyzed in this section was developed in order to measure a set of potential outcomes of schooling that might be considered part of the "latent curriculum". There are 40 items in this questionnaire, and these items were classified into four subscales with 10 items per scale. The specific subscales were Punctuality, Honesty, Cooperation and Curiosity. The items are given in Table 1. The students were asked to respond with a <u>no</u> if the item did not represent their feelings or attitudes, and with a <u>yes</u> if the item did reflect their feelings. There were 700 elementary school students in the sample that was analyzed.

INSERT TABLE 1 HERE

A stepwise full-information item factor analysis was performed specifying a four factor solution for the School Affect Data. The chi-square fit statistics of each solution and their differences are presented in Table 2. Although the reduction of the chi-square fit statistics seems to suggest that a model with more than four dimensions may provide a better fit to the data, a careful examination of the fourth factor loadings revealed that these loadings were minor and no interpretable or distinctive factor pattern was found. Therefore, we have chosen the three factor solution as an appropriate model to describe the behaviour of the School Affect Data. The three dimensional varimax factor loadings are presented in Table 3.

INSERT TABLES 2 AND 3 HERE

The factor patterns in Table 3 shows that the first factor loadings are generally high on most of the Honesty and Cooperation items. The following items have noticeably high factor loadings on the first dimension:

1. I know when I am being honest and dishonest.
2. I understand that being honest is important.
10. It is important to be honest with strangers, my friends and my family.
17. I believe that working with other students is more important than competing with them.
20. I can tell when it is better to work together with other students than to compete with them.

We call the first factor characterized by the above items, interpersonal relations. It seems to represent the interactions between students within the classroom.

High factor loadings are found on the second factor for the following items:

25. I try to find out all I can about the subjects that the teacher talks about in class.

26. I am always asking questions and trying to find out more about my classwork.

27. Being curious about my classwork is important to me.

28. I enjoy looking for and trying out new ideas and projects.

30. I have a need to know as much as possible about myself and my world.

39. Being on time for class is very important to me.

The items with high loadings on this factor come primarily from the Curiosity scale. These items seem to represent students' attitude toward school learning. We therefore call the second factor, <u>active participation</u>.

Finally, the third factor has loadings that are distinctively high on the following items:

37. I finish my classroom assignments when they are due.

38. I turn in my homework on time.

40. I finish my classwork on time, even when the teacher is not around.

6. I keep my eyes on my own work in the classroom.

The items with high loadings on this factor come primarily from the Punctuality scale. Like the second factor, the third factor seems to indicate students' diligence in school work. However, this third factor represents a more passive attitude toward school learning than the active participation factor, since all the items above illustrate students' behavior in relation to assigned tasks. For this reason, we call this factor, studious attitude.

The full-information item factor analysis provides an objective basis for clarifying the distinction between what the item writer intends to measure and what the items actually appear to measure. At the stage of test item construction, the full-information factor analysis provides a powerful method for researchers to examine the construct validity of each item. For example, item 13, "I do not compete with other students for good grades" has low factor loadings on all three dimensions. Less that half of respondents endorsed this item. This item also has low biserial and point-biserial coefficients, 0.132 and 0.104 respectively. In fact, the statement of this item is not universally considered as the positive attitude of school learning. In addition, the negative wording of this statement may have confused subjects' responses. In this way, the full-information factor analysis is quite sensitive to ill-behaved items.

Despite a small lack of accordance on a few items which are discussed later in this paper, as a whole, the agreement between the predefined four scales and the three major factors is relatively high. The Honesty and Cooperation items define an interpersonal relations factor, the Curiosity items define an active participation factor, and the Punctuality items define a studious attitude factor. As shown in Table 4, the correlation coefficients between the total scores of the four original scales (the raw score scales), and the EAP scores for three dimensions confirm this overall agreement. The raw score scales are simply the summation of the 0 or 1 dichotomous responses over the items in a specific scale, such as the items representing Honesty, Cooperation, Curiosity and Punctuality. On the other hand, the EAP scores corresponding to each dimension were computed based on the item response model with estimated slope and scale parameters, after the varimax rotation.

INSERT TABLE 4 HERE

Traditional data analysis usually deals with the total score of pre-established psychological scales. The utilization of the EAP scores, however has advantages over raw scores for the following reasons:

1. The EAP scores are computed based on all the information available in the subjects response patterns. Therefore, the EAP scores are more continous than the raw score scales. This high continuity enhances the power of the statistical tests. The continuity of EAP scores can be further increased by additional items and dimensions.

2. The EAP scores reflect the significant contribution of each item of whole test to a specific dimension or factor. On the other hand, each of the raw score scales reflect only a portion of the items in the whole test. Therefore, the raw score scales are subject to the potential misclassification of items from the pre-established scales. For example, item 6 states "I keep my eyes on my work in the classroom", and is classified as an item in the Honesty scale. However, this item has a low

factor loading on the interpersonal relations factor and a rather high factor loading on the studious attitude factor. Considering this item as equal to the other items in the Honesty Scale may distort the conclusions drawn from further analyses of the data.

3. As shown in Table 4, the correlation coefficients among the EAP scores are quite small compared to the correlation coefficients among raw score scales. The orthogonality of the EAP scores over the multidimensional space indicates that the scores represent distinctive characteristics of the subjects.

4. Detecting items with poor construct validity becomes considerably easier when we use full-information factor analysis. Even though those items are included in the further analyses, the result is less affected if the EAP scores are used.

5. The raw score scales are not computable even if one of the responses to the items in a scale is missing. However, the EAP scores can be computed regardless of missing responses. Actually, as shown in Table 5, the raw scores of 50 subjects were excluded from the further data analysis because of their missing responses.

INSERT TABLE 5 HERE

Discussion of Multivariate Analysis of Raw Scores and EAP Scores

In order to illustrate some of the advantages of the EAP scores over the use of raw scores, a multivariate analysis of variance was conducted using each type of score.

Two major factors were included in the analysis. The first factor is grade level, and the second factor is the sex of the student. The grade level gives an indication of the effect of quantity of schooling on the affective outcomes of schooling.

The sex of the student was included because there has been evidence that girls and boys may be learning different lessons in school.

The cell and marginal frequencies for the sample based on the results of the raw scores are given in Table 5. The observed cell and marginal means are given in Table 6. The cell and marginal frequencies for the EAP scores are given in Table 7, while the observed cell and marginal means for these scores are given in Table 8. The sample size for the raw scores is 650 because 50 of the students had missing responses to one or more items, while the sample size for the EAP scores is 700.

INSERT TABLES 6, 7 AND 8 HERE

Table 9 provides a summary of the univariate and multivariate analysis of variance for the raw scores. There are no significant interactions between grade and sex for the four dependent variables. Grade level has a significant effect on Cooperation and Curiosity, but not on Honesty or Punctuality. Overall, there appears to be an increase in the students reported levels of Cooperation, and a decrease in their Curiosity during elementary school. The sex of the student has a significant effect on Honesty, Cooperation and Punctuality. The girls have higher means on all of the scales. Although there are no significant interactions between grade level and sex, an examination of the cell means suggest that there may be slight differences in the patterns across grades for girls and boys on the cooperation scale ($p<.0869$). The boys show a clear decline from grades 3 to 7. The girls appear to become less cooperative from grade 3 to grade 5, and then to report that they become more cooperative from grade 5 to grade 7. It would be interesting to examine this data for cubic trend across grades.

INSERT TABLE 9 HERE

The results for the univariate and multivariate analysis of variance for the EAP scores are summarized in Table 10. There are no significant interactions for the grade level or sex effect for the EAP scores. Grade level has a signifant effect on the *interpersonal relations factor* and on the *active participation factor*, but not on the studious attitude factor. An examination of the marginal means by grade level indicates that the students show a increase on the *interpersonal relations factor*, and a decrease on the *active participation factor*. Sex has a significant effect on all three factors, and the girls have higher levels on each.

INSERT TABLE 10 HERE

In comparing the results of the analyses based on the EAP scores and the raw scores, there appears to be a reasonable amount of agreement. The similarities between the two analyses is related to the amount of agreement between the a priori classification of the items into the four scales, and the results of the full-information item factor analysis.

It is also of interest to note that the p-values are smaller for the analyses using the EAP scores which indicates that the statistical tests are more sensitive with the EAP scores. This is related to the increase in the information that is availabe by using all the data available in the response patterns which is not used when raw scores are analyzed.

In summary, the interpretation of the multivariate analysis is simplified with the EAP scores where there are fewer concepts to discuss. The orthogonality of the EAP scales also facilitates the interpretation of the results, since they represent a better index of the constructs. The EAP scores better reflect what the test items actually measure, and they are sensitive to test item behaviors. Therefore, the construct validation of the psychological measurement based on the full-information item factor analysis is strongly recommended in the initial item preparation stage.

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FIG. 1 PLOT OF θ_1 VS. $\hat{\tau}_1$ S2000

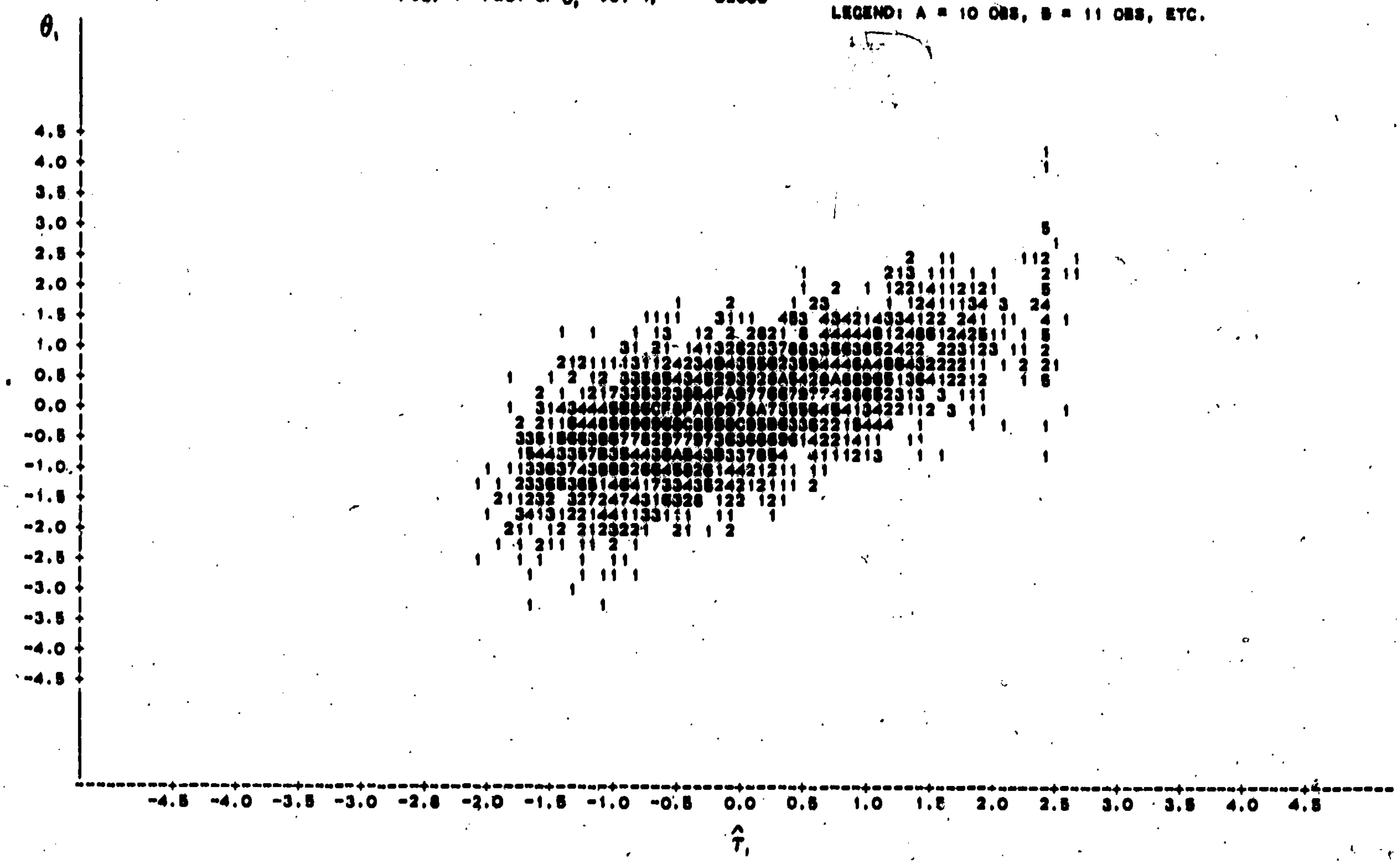

FIG. 2 PLOT OF θ_2 VS. $\hat{\tau}_2$ S2000

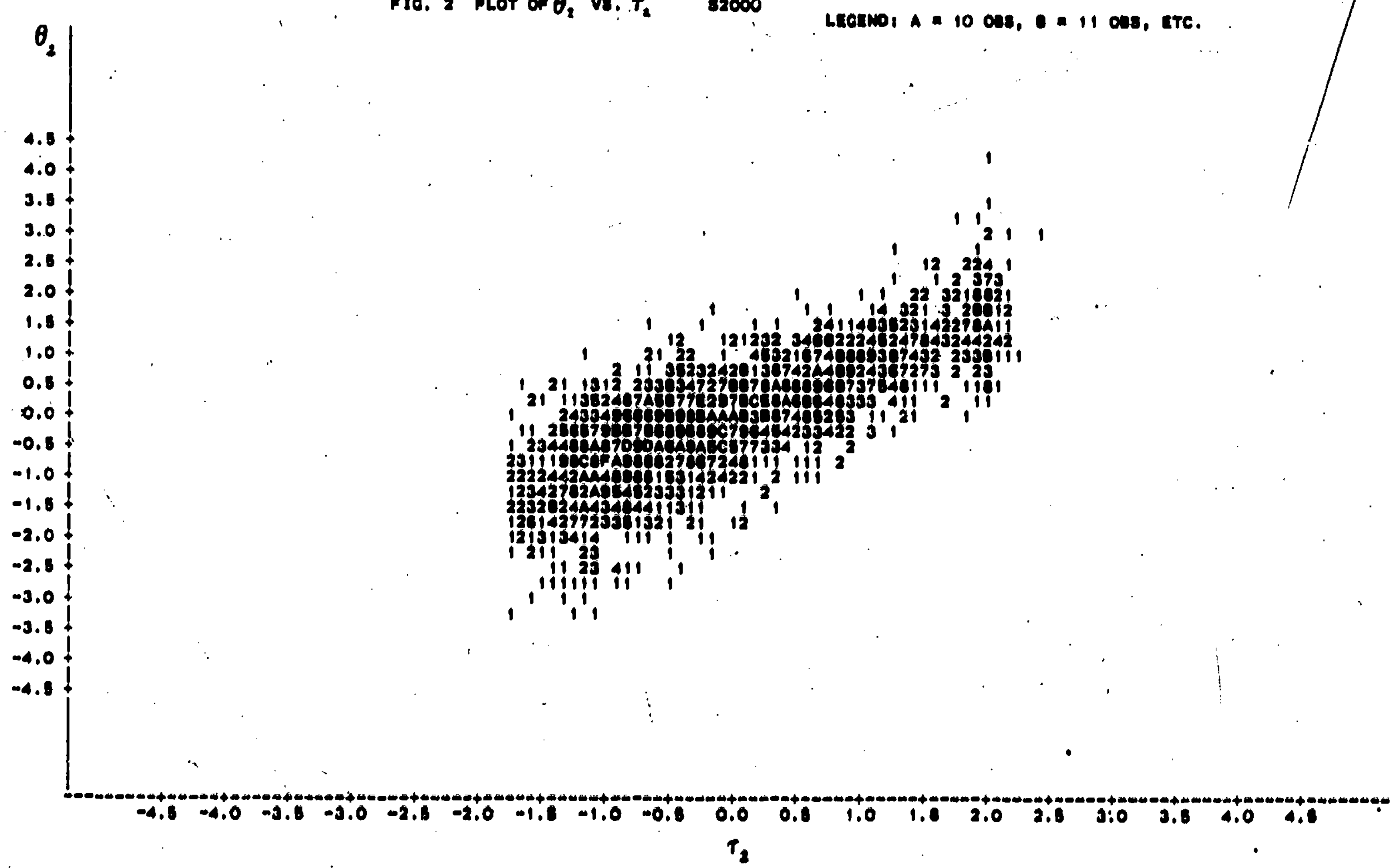

FIG. 3 MLE ESTIMATES FROM EVEN AND ODD ITEMS

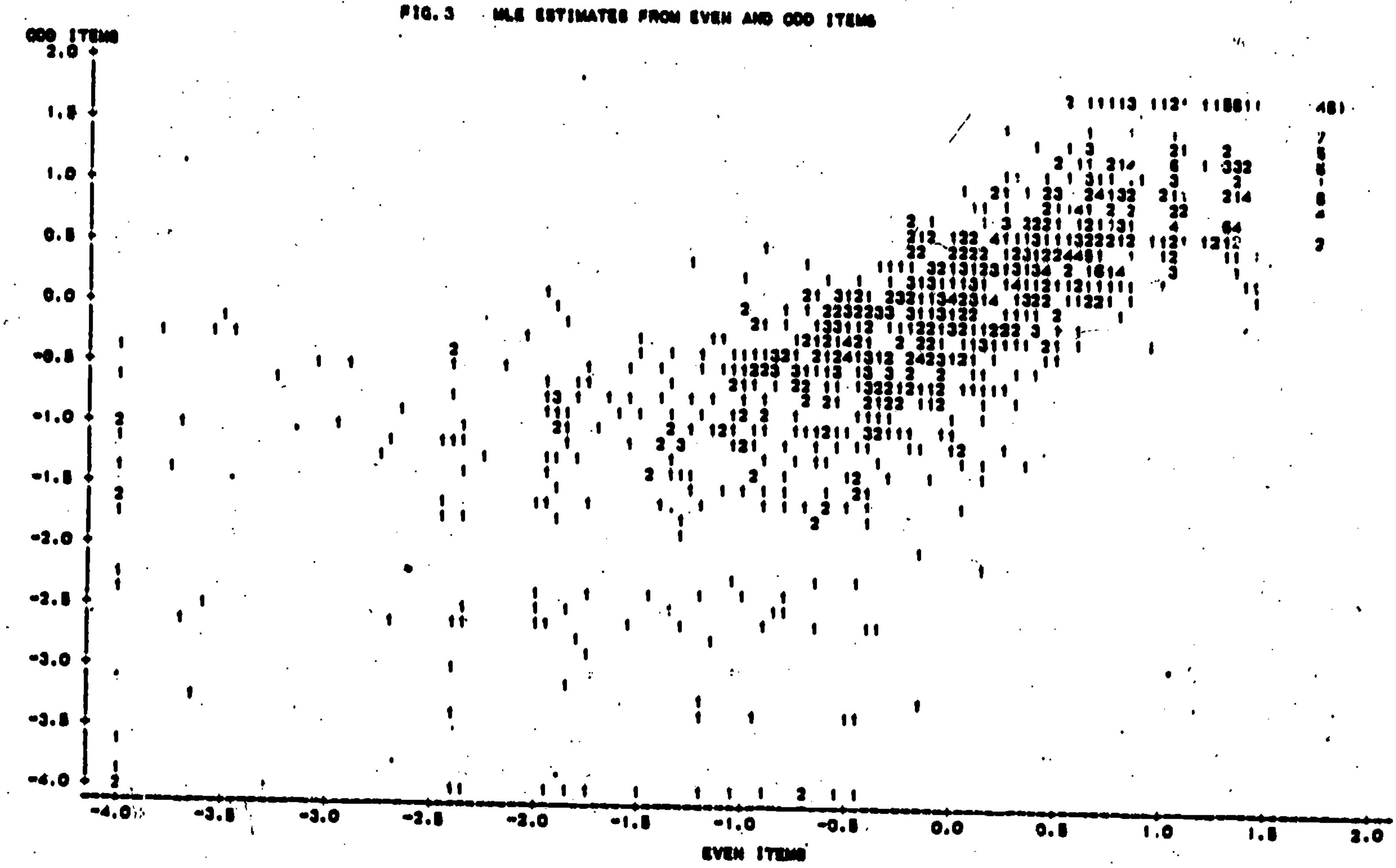

FIG. 4 EAP ESTIMATES FROM EVEN AND ODD ITEMS

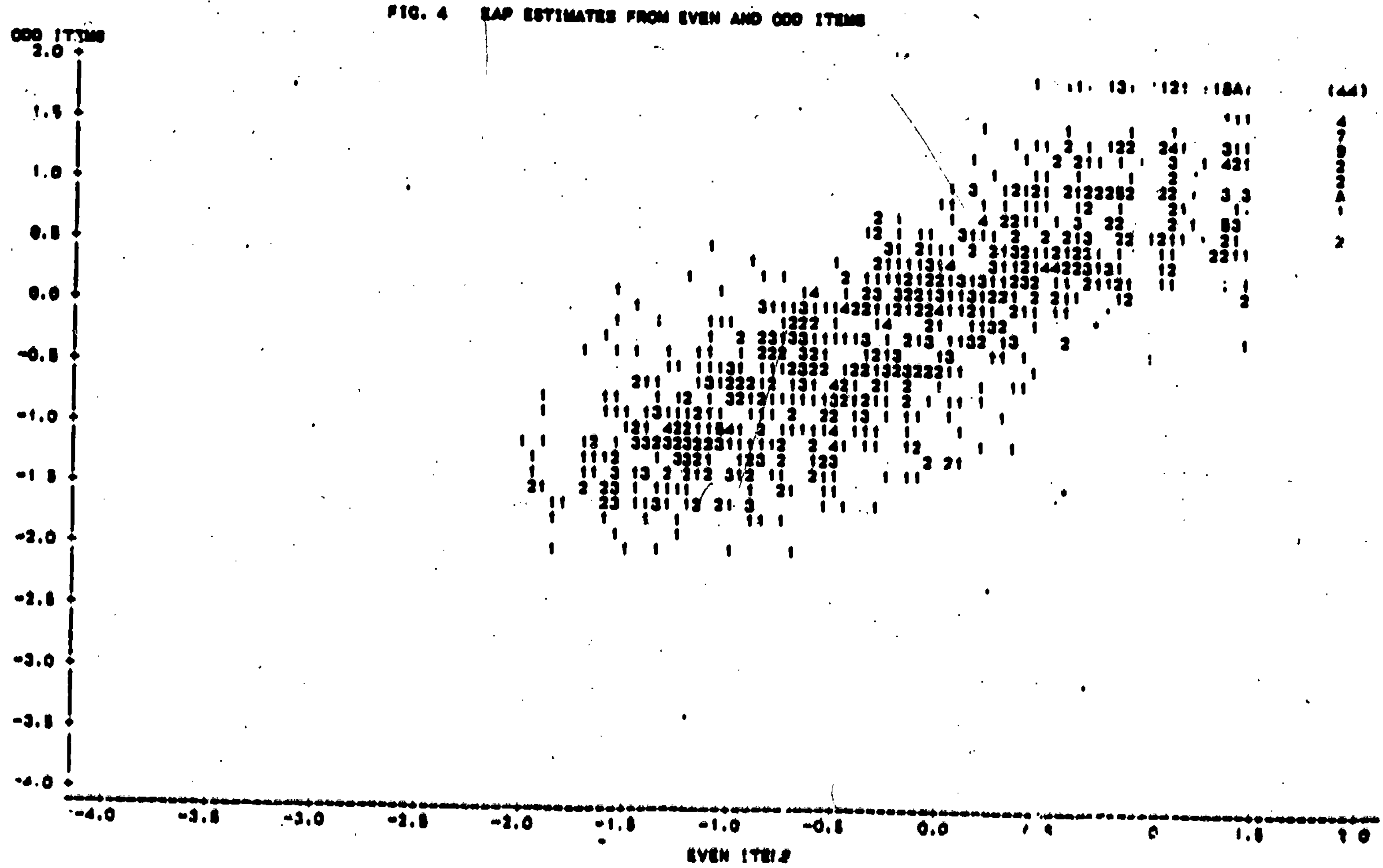

Table 1
Affective Outcomes of Schooling Items

	Honesty		Cooperation
1	I know when I am being honest and dishonest.	11	I know that in some things working with other students can be better than working alone.
2	I understand that being honest is important.	12	I know when to cooperate and when to compete with my classmates.
3	I know that cheating on classwork is wrong.	13	I do not compete with other students for good grades.
4	I do not copy answers from other students.	14	I help other students who do not understand their classwork.
5	I tell the truth when questioned by the teacher.	15	I work with my friends on my homework.
6	I keep my eyes on my own work in the classroom.	16	I get along with other students when we are working together in a group.
7	Being honest is very important to me.	17	I believe that working with other students is more important than competing with them.
8	I am honest in the classroom, even when the teacher is not around.	18	I enjoy working on projects with other students.
9	Being honest can lead to good and bad things.	19	I believe that if my classmates and I work together that most of us could get good grades.
10	It is important to me to be honest with strangers, my friends and my family.	20	I can tell when it is better to work together with other students than to compete with them.

Note. The students responded with a no or yes to each item.

Table 1 (Cont.)
Affective Outcomes of Schooling Items

Curiosity		Punctuality	
21	I know that learning about new things is important.	31	I know that I am expected to come to class on time.
22	My classroom offers me a wide variety of things to do and learn.	32	I understand why being on time for class is important.
23	I know how to find out about anything I may want to know.	33	I know that my classwork is due at a certain time.
24	I ask questions when I do not understand what my teacher is doing.	34	I am in my seat when the bell rings in the morning.
25	I try to find out all I can about the subjects that the teacher talks about in class.	35	I try to come to class on time.
26	I am always asking questions and trying to find out more about my classwork.	36	I am ready to begin class when the bell rings in the morning.
27	Being curious about my classwork is important to me.	37	I finish my classroom assignments when they are due.
28	I enjoy looking for and trying out new ideas and projects.	38	I turn in my homework on time.
29	I get excited about the topics discussed in my classroom.	39	Being on time for class is very important to me.
30	I have a need to know as much as possible about myself and my world.	40	I finish my classwork on time, even when the teacher is not around.

Note. The students responded with a no or yes to each item.

Table 2
Reduction in Chi-Square Fit Statistics

Adding Factor	Reduction in Chi-Square	Degrees of Freedom
Second factor	349.04	39
Third factor	259.25	38
Fourth factor	171.35	37

Table 3

Varimax Factor Loadings for the Three Factor Solution

Scale	Item	Threshold	Factors First	Second	Third
Honesty	1	-1.564	.595	-.011	.078
	2	-1.643	.500	.253	.160
	3	-1.361	.329	.262	.195
	4	-.230	.278	-.028	.118
	5	-1.001	.244	.229	.407
	6	-.967	.131	.241	.502
	7	-1.432	.412	.371	.343
	8	-.566	.253	.317	.465
	9	-1.164	.283	-.051	.097
	10	-.860	.512	.066	.269
Cooperation	11	-.757	.454	.024	.020
	12	-1.113	.348	.252	.134
	13	.238	.095	-.212	.169
	14	-.848	.303	.152	.254
	15	.197	.208	-.006	-.084
	16	-1.113	.431	-.009	.152
	17	-.801	.541	.032	.116
	18	-.988	.249	.356	.060
	19	-.660	.267	.164	-.109
	20	-1.088	.487	.219	.279
Curiosity	21	-1.815	.219	.321	.357
	22	-.591	.146	.340	.172
	23	-.519	.069	.258	.094
	24	-.945	-.021	.494	.052
	25	-.633	-.101	.703	.100
	26	-.181	-.116	.612	-.018
	27	-.846	.136	.541	.125
	28	-.954	.163	.580	.097
	29	.210	-.087	.437	.017
	30	-1.225	.157	.519	.217
Punctuality	31	-2.062	.262	.225	.292
	32	-1.267	.271	.497	.252
	33	-1.473	.425	.220	.231
	34	-.525	.320	.158	.385
	35	-1.791	.272	.372	.203
	36	-.824	.196	.401	.431
	37	-.731	.015	.015	.838
	38	-.906	.208	.105	.802
	39	-1.065	.256	.509	.399
	40	-.448	-.002	.061	.855

Table 4
Correlations of Raw Score Scales and the EAP Scores
(Sample sizes in parentheses)

	HO	CO	CU	PU	EAP $\tilde{\theta}_1$	EAP $\tilde{\theta}_2$	EAP $\tilde{\theta}_3$
Honesty	1.000 (687)						
Cooperation	.331 (670)	1.000 (678)					
Curiosity	.272 (667)	.191 (660)	1.000 (672)				
Punctuality	.455 (681)	.254 (672)	.324 (667)	1.000 (688)			
EAP $\tilde{\theta}_1$	.617 (687)	.751 (678)	.098 (672)	.306 (688)	1.000 (700)		
EAP $\tilde{\theta}_2$	.302 (687)	.196 (678)	.910 (672)	.353 (688)	.161 (700)	1.000 (700)	
EAP $\tilde{\theta}_3$	.470 (687)	.148 (678)	.152 (672)	.823 (688)	.143 (700)	.094 (700)	1.000 (700)

Table 5
Cell and Marginal Frequencies for Total Scale Scores

Grade	Sex Boys	Girls	Total
3	91	104	195
5	132	112	244
7	106	105	211
Total	329	321	650

Table 6
Observed Cell and Marginal Means and Standard Deviations of Raw Score Scales

	Sex							
	Boys				Girls			
Grade	HO	CO	CU	PU	HO	CO	CU	PU
3	8.187 (1.61)	7.000 (1.65)	7.978 (1.69)	8.330 (1.50)	8.519 (1.59)	7.846 (1.41)	8.385 (1.32)	8.673 (1.46)
5	8.258 (1.54)	7.106 (1.92)	7.242 (2.00)	8.273 (1.93)	8.652 (1.44)	7.313 (1.71)	7.366 (1.95)	8.598 (1.70)
7	8.340 (1.58)	7.528 (1.51)	7.066 (1.95)	8.160 (2.18)	8.686 (1.40)	7.743 (1.73)	7.029 (2.24)	8.524 (1.78)

Marginal Means by Grade Level

Grade	HO	CO	CU	PU
3	8.364	7.451	8.195	8.513
5	8.439	7.201	7.299	8.422
7	8.512	7.635	7.047	8.341

Marginal Means by Sex

Sex	HO	CO	CU	PU
Boys	8.264	7.213	7.389	8.252
Girls	8.620	7.626	7.586	8.598

Table 7
Cell nd Marginal Frequencies for The EAP Scores

	Sex		
Grade	Boys	Girls	Total
3	100	111	211
5	141	123	264
7	117	108	225
Total	358	342	700

Table 8
Observed Cell and Marginal Means and Standard Deviations of The EAP Scores

	Sex					
	Boys			Girls		
Grade	$\tilde{\theta}_1$	$\tilde{\theta}_2$	$\tilde{\theta}_3$	$\tilde{\theta}_1$	$\tilde{\theta}_2$	$\tilde{\theta}_3$
3	-.277 (.779)	.194 (.770)	-.097 (.717)	.049 (.853)	.401 (.607)	.047 (.731)
5	-.171 (.750)	-.145 (.865)	.025 (.759)	-.010 (.762)	-.017 (.831)	.148 (.809)
7	.168 (.674)	-.212 (.858)	-.121 (.895)	.290 (.706)	-.184 (.924)	.029 (.886)

Marginal Means by Grade Level

Grade	$\tilde{\theta}_1$	$\tilde{\theta}_2$	$\tilde{\theta}_3$
3	-.106	.303	-.021
5	-.096	-.085	.082
7	.227	-.198	-.049

Marginal Means by Sex

Sex	$\tilde{\theta}_1$	$\tilde{\theta}_2$	$\tilde{\theta}_3$
Boys	-.090	-.072	-.057
Girls	.104	.066	.078

Table 9
Univariate and Multivariate Analysis of Variance (Raw Scores)

Source	DF	Dep. Var.	SS	Univariate F	Univariate p less than	Multivariate F (DF)	Multivariate p less than
Constant	1	HO	46301.840				
		CO	35756.986				
		CU	36427.625				
		PU	46116.346				
Grade, eliminating Constant	2	HO	2.213	.476	.6215	7.239	.0001***
		CO	21.666	3.866	.0215*	(8,1282)	
		CU	147.095	20.537	.0001***		
		PU	2.984	.467	.6273		
Sex, eliminating Constant & Grade	1	HO	20.979	9.026	.0028**	3.680	.0057**
		CO	26.015	9.284	.0025**	(4,641)	
		CU	3.938	1.100	.2948		
		PU	19.069	5.966	.0149*		
Sex, eliminating Constant	1	HO	20.534	8.834	.0031**	3.762	.0050**
		CO	27.767	9.909	.0018**	(4,641)	
		CU	6.281	1.754	.1859		
		PU	19.434	6.080	.0140*		
Grade, eliminating Sex & Constant	2	HO	2.658	.572	.5648	7.195	.0001***
		CO	19.914	3.553	.0292*	(8,1282)	
		CU	144.752	20.210	.0001***		
		PU	2.619	.410	.6641		
Grade & Sex, eliminating all main effects	2	HO	.118	.025	.9750	.8822	.5308
		CO	13.745	2.453	.0869	(8,1282)	
		CU	5.086	.710	.4921		
		PU	.041	.006	.9937		
Group Means	6	HO	46325.150				
		CO	35818.412				
		CU	36583.744				
		PU	46138.440				
Within Groups	644	HO	1496.850				
		CO	1804.588				
		CU	2306.256				
		PU	2058.560				
Total	650	HO	47822.000				
		CO	37623.000				
		CU	38890.000				
		PU	48197.000				

* $.05 > p \geq .01$
** $.01 > p \geq .001$
*** $.001 > p$

Table 10
Univariate and Multivariate Analysis of Variance (EAP Scores)

Source	DF	Dep. Var.	SS	Univariate F	Univariate p less than	Multivariate F (DF)	Multivariate p less than
Constant	1	$\tilde{\theta}_1$	.016				
		$\tilde{\theta}_2$	.015				
		$\tilde{\theta}_3$	.056				
Grade, eliminating Constant	2	$\tilde{\theta}_1$	16.322	14.321	.0001***	15.120	.0001***
		$\tilde{\theta}_2$	30.125	22.482	.0001***	(6,1384)	
		$\tilde{\theta}_3$	2.360	1.832	.1609		
Sex, eliminating Constant & Grade	1	$\tilde{\theta}_1$	6.856	12.031	.0006***	5.499	.0010**
		$\tilde{\theta}_2$	2.494	3.723	.0541	(3,692)	
		$\tilde{\theta}_3$	3.315	5.147	.0236*		
Sex, eliminating Constant	1	$\tilde{\theta}_1$	6.564	11.519	.0008***	5.563	.0009***
		$\tilde{\theta}_2$	3.334	4.976	.0261*	(3,692)	
		$\tilde{\theta}_3$	3.153	4.895	.0273*		
Grade, eliminating Sex & Constant	2	$\tilde{\theta}_1$	16.614	14.577	.0001***	15.082	.0001***
		$\tilde{\theta}_2$	29.285	21.856	.0001***	(6,1384)	
		$\tilde{\theta}_3$	2.522	1.958	.1419		
Grade & Sex, eliminating all main effects	2	$\tilde{\theta}_1$	1.277	1.121	.3267	.5302	.7857
		$\tilde{\theta}_2$	.892	.666	.5144	(6,1384)	
		$\tilde{\theta}_3$	.024	.019	.9816		
Group Means	6	$\tilde{\theta}_1$	24.471				
		$\tilde{\theta}_2$	33.526				
		$\tilde{\theta}_3$	5.755				
Within Groups	694	$\tilde{\theta}_1$	395.483				
		$\tilde{\theta}_2$	464.951				
		$\tilde{\theta}_3$	446.969				
Total	700	$\tilde{\theta}_1$	419.954				
		$\tilde{\theta}_2$	498.477				
		$\tilde{\theta}_3$	452.724				

* $.05 > p \geq .01$
** $.01 > p \geq .001$
*** $.001 > p$