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ABSTRACT

Within aptitude areas (Mechanical, Administrative, General, or Electronic) in the Air Force, some technical schools require higher levels of aptitude for admission than do others (for example, there are G10 schools, G60 schools, and G80 schools based on General test scores in th 10th, 60th, and 80th percentiles respectively). The schools, however, give grades on a scale from 70 to 100, regardless of the difficulty of the school curriculum. This means that a score of 82 in a G40 school is recorded the same as an 82 in a G80 school although the scores in a G80 school must indicate a higher level of performance than the same score does in the G10 school. This study is an evaluation of a method of adjusting technical school grades issued by schools of varying difficulty so that a new criterion is formed with all school grades adjusted to the same metric. This new criterion was then used to recompute aptitude indexes, which were compared with aptitude indexes computed in the conventional manner. The new aptitude indexes predicted school grades in a cross-validation sample better than did conventional aptitude indexes. (Author/BW)

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AIR FORCE

HUMAN RESOURCES

WEIGHTING OF APTITUDE COMPONENTS BASED ON DIFFERENCES IN TECHNICAL SCHOOL DIFFICULTY

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LABORATORY

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This report has been reviewed by the Office of Public Affairs (PA) and is releasable to the National Technical Information Service (NTIS). At NTIS, it will be available to the general public, including foreign nations.

This technical report has been reviewed and is approved for publication.

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Within aptitude areas (Mechanical, Administrative, General, or Electronic) in the Air Force, some technical schools require higher levels of aptitude for admission than do others (for example, there are G40 schools, G60 schools, and G80 schools based on General test scores in the 40th, 60th, and 80th percentiles respectively). The schools, however, give grades on a scale from 70 to 100, regardless of the difficulty of the school curriculum. This means that a score of 82 in a G40 school is recorded the same as an 82 in a G80 school, although the score in a G80 school must indicate a higher level of performance than the same score does in the G40 school. When validities are computed across an entire aptitude area, the different meanings of identical numbers across schools of varying difficulty must confound the results.

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This study is an evaluation of a method of adjusting technical school grades issued by schools of varying difficulty so that a new criterion is formed with all school grades adjusted to the same metric. This new criterion was then used to recompute aptitude indexes, which were compared with aptitude indexes computed in the conventional manner. The new aptitude indexes predicted school grades in a cross-validation sample better than did the conventional aptitude indexes.

PREFACE

This study was conducted under Task 771918, Selection and Classification Technologies. The research focuses on the development of procedures and techniques to refine and improve measurement devices used in the Air Force operational testing program.

This work represents an attempt to refine the aptitude indexes of the Armed Services Vocational Aptitude Battery (ASVAB), thereby improving their predictive accuracy and consequently the utility of selection measures. This effort supports the subthrust area Assessment of Personnel Qualifications, under the major thrust area of Manpower and Force Management.

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WEIGHTING OF APTITUDE COMPONENTS BASED ON DIFFERENCES IN TECHNICAL SCHOOL DIFFICULTY

I. BACKGROUND AND INTRODUCTION

The use of the official aptitude battery (called by various names over the past three decades) for selection and classification of Air Force enlisted personnel has always taken the form of computation and interpretation of four or more Aptitude Indexes (AIs) (Weeks, Mullins, & Vitola, 1975). The use of AIs appeared in the first Air Force aptitude battery (AC-1A). It was not administratively feasible in 1948 to produce a unique composite score for each Air Force job, but it was assumed that differential aptitude composites were desirable. Job clusters were developed on the basis of subjective judgment and job analysis data. Through study of test results, scientists formed clusters of tests (AIs) which were reasonably homogeneous internally and predictive of success in schools in the separate job clusters.

During succeeding years, various changes in composition of the AIs have been made, mostly by administrative fiat, so that at the present time the current enlisted aptitude battery produces four Air Force AIs—Mechanical (M), Administrative (A), General (G), and Electronic (E). Along the way, a great deal of research has been done on the enlisted aptitude battery, but few studies questioned the effectiveness of the concept of M, A, G, and E aptitude indexes or explored novel ways of weighting subtests to produce the M, A, G, and E composites. This study addresses the utility of a different method for weighting the M, A, G, and E composites.

Historically, subtest weighting has been accomplished partly by science and partly by artistry. Through various multiple correlational techniques, an optimum weight has been derived within each Air Force Specialty for each subtest score against final technical school grade for that specialty. Then the sets of weights for specialties have been scrutinized within a particular aptitude area (say, M), looking for a minimal set of predictors which consistently exhibit positive non-trivial weights across the entire area. When such a set has been found (three or four predictors), the weights are all rounded to 1.0, and again multiple correlation coefficients are computed between school grades and these unit-weighted predictor variables to see if the validities are holding up after conversion from optimum weights to unit weights. Ordinarily, little is lost by converting to unit weighting (see Wainer, 1976).

One problem, however, has been recognized with this system. Different schools within each aptitude area require different AI levels to qualify for entry. For example, some A schools require only a score of 40th percentile for admission, while others require the 80th percentile. Both schools, however, give grades on the same apparent scale, from 70 to 100, even though the A80 school is undoubtedly much more difficult that the A40 school. Therefore, a final school grade of 82 would refer to a lesser accomplishment in the A40 school than it would in the A80 school. When validities are computed and predictor weights assigned across entire aptitude areas regardless of school level (see Figure 1), some method is needed for adjusting school grades in individual schools upward or downward as a function of the prerequisite levels of ability (A40, A50, . . . A80). Such a method would ensure that graduates of A40 and A80 schools have criterion scores based on the same metric. In short, if it could be done, predictor weights for subtests would be more accurate, and AI scores could be computed which would be more efficient than they are now. The problem, then, is how to estimate what the school grade of the A80 students would have been if they had taken the A40 course and if there had not been a ceiling score of 100 on school grades.

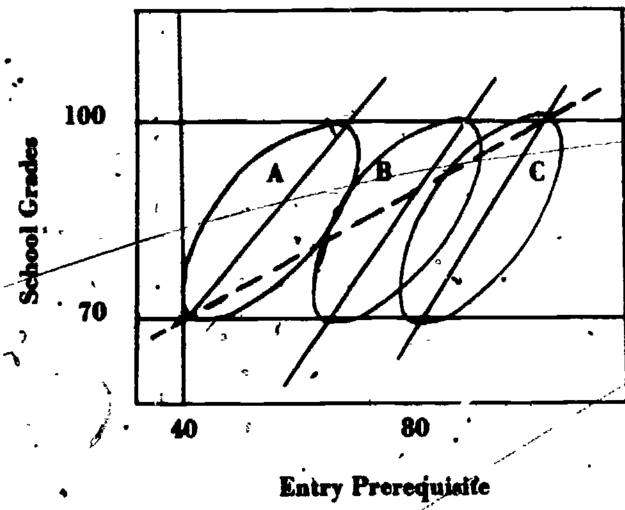


Figure 1. Schematic representation of depressing effect of similar criterion range on overall validity coefficient computed across school requiring different levels of aptitude.

When restated in this form, the problem almost resolves itself. The solution is to find a constant that can be added to the school grades of A80 students to reflect the difference in difficulty between the A40 and A80 schools. Such a constant should improve the situation in the manner depicted in Figures 1 and 2. The computation of this constant requires only that the mean school grade of the A40 school be known and that an estimate can be made of the mean school grade the A80 students would have earned if they had attended the A40 school and if the 100 score ceiling were removed. Such an estimate can be made reasonably well by computing the best AI in the A40 school from available predictor information. This AI is then used to predict the grades of members of the A80 group. The difference between the mean of the observed criterion grades of the A40 group and the mean of the predicted grades of the A80 group provides the required constant. This constant is then added to the criterion grade of each subject in the A80 group to provide a raw criterion metric so that grades of all students (both A40 and A80) are arranged on the same criterion scale.

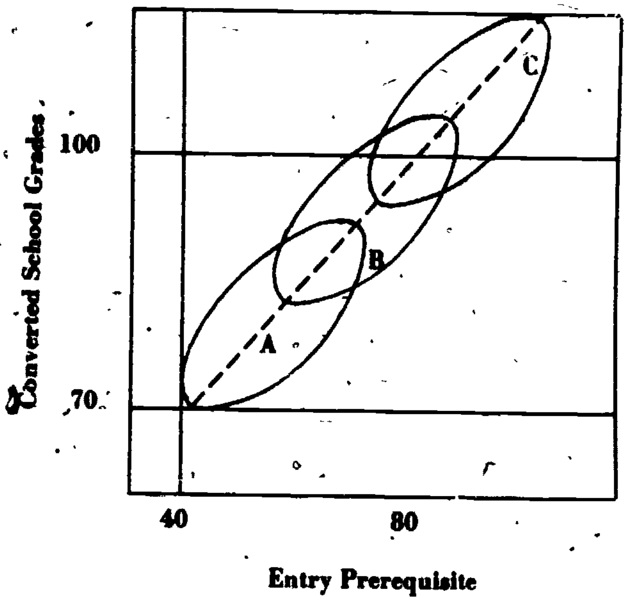
The formula to derive the new criterion K score is as follows:

$$K_j = G_j + (\bar{c}_T - \bar{c}_B)$$

where

K_j = the transformed grade score of person j

G_j = the observed grade score of person j



— — = Line of best fit for entire aptitude area
A = A40 entrance prerequisite
B = A60 entrance prerequisite
C = A80 entrance prerequisite

Figure 2. **Schematic representation of higher validity coefficient attainable if different level schools are placed on same criterion metric by adding constants.**

$\bar{c}_B$ = the mean of the composite scores generated for students in the Base group (the group in which the prediction composite is generated—i.e., the A40 group in the above example).

$\bar{c}_T$ = the mean of the composite scores generated for subjects in a Target group by applying weights developed in the Base group (the Target group is the group to which the criterion grade correction will be applied. In the above example, A80 would be the Target group).

When the scores on the K criterion have been computed, the situation depicted in Figure 2 will have been achieved, and an adjusted criterion will have become available for use in developing new weights for the available predictor variables. The new weights can be used to establish a new aptitude composite which may reasonably be expected to predict success throughout the aptitude area, disregarding level, better than any set of weights computed in the conventional way.

Two sets of weights are computed. The first set comes from predicting the actual grades on just the A40 group and is done only as an intermediate step to determine the constant used to adjust the grades of the A80 group. The second set of weights comes from predicting a combination of the actual grades on the A40 group and the adjusted grades on the A80 group. This second set of weights defines the new aptitude composite.

After the new weights (against the K criterion) have been established and composite aptitude scores have been computed for all students in the study, it is necessary to check empirically to see whether the new composites really do predict actual school grades better than do the old ones. The objective of this study was to develop new weights for aptitude composites computed from K-criterion scores for a sample of the population and to cross-apply these weights to another sample.

II. APPROACH

Sample Population

The sample consisted of all airmen entering the Air Force between January 1977 and September 1979, on whom subtest and AI scores on Armed Services Vocational Aptitude Battery (ASVAB) Forms 5, 6, or 7 and numerical technical training final school grades were available. School failures were omitted from the sample, as well as all subjects in schools where the total number of graduates during this 2-year period was less than 50. Total N for the sample after all necessary deletions was 88,199. Of these, 19,715 were graduates of schools requiring multiple aptitude prerequisites (e.g., E80 and M60), and 68,484 were from 119 schools with only a single prerequisite (e.g., A60). The 19,715 subjects in schools with multiple prerequisites were arbitrarily called X, and all computations and data manipulations applied to the M, the A, the G, and the E subjects were also applied to the X subjects (even though this group consisted of M, A, G, and E subjects intermingled).

The subjects in each school were randomly divided equally into a computing (C) subsample and a cross-validation (V) subsample. Then, within each subsample, schools were combined to form the groups shown in Table 1.

Table 1. **Groups by Aptitude Area and by Entry Level**

Group	N(C+V)	Group	N(C+V)	Group	N(C+V)
M40	8,395[a]	G40	3,530	E50	1,852
M50	8,079	G45	14,271[a]	E60	1,134
A40	7,259[a]	G50	154	E80	10,322[a]
A50	224	G60	8,710	X40	5,078
A60	2,251	G65	121	X50	1,266
A70	205	G80	773	X60	13,371[a]
A80	1,204				

[a]Base group. All others are Target groups.

Predictor/Criterion Variables

The following variables were available (or were computed) on each subject:

1. Technical school final grades, graduates only.
2. ASVAB subtest score—Numerical Operations
3. ASVAB subtest score—Attention to Detail

4. ASVAB subtest score—Word Knowledge
5. ASVAB subtest score—Arithmetic Reasoning
6. ASVAB subtest score—Space Perception
7. ASVAB subtest score—Mechanical Comprehension
8. ASVAB subtest score—Shop Information
9. ASVAB subtest score—Auto Information
10. ASVAB subtest score—Electronics Information
11. ASVAB subtest score—General Information
12. ASVAB subtest score—Math Knowledge
13. ASVAB subtest score—General Science
14. Mechanical AI, as conventionally derived.[1]
15. Administrative AI, as conventionally derived.[1]
16. General AI, as conventionally derived.[1]
17. Electronic AI, as conventionally derived.[1]

18-59. Educational variables. These variables were dichotomous, scored 1 if the subject had successfully completed a specified public-school course, zero otherwise.

60-64. Prediction composites C1M, C1A, C1G, C1E, and C1X, computed against the K criterion using only the ASVAB subtest scores (Variables 2—13).

65-69. Prediction composites C2M, C2A, C2G, C2E, and C2X, computed against the K criterion using the subtest scores and the educational variables (Variables 2—13, 18—59).

Method

The K criterion was computed in the C subsample of the M Base Group (M40 schools), and applied in the Target Groups (only one in this case) of that aptitude area to get the constants for correcting the final school grades of each subject so that all members of M schools were placed on the same criterion (the K criterion) metric.

This procedure yielded a single criterion for all members of the M aptitude area, regardless of level. The levels were then combined, and within the M aptitude area, another R^2 was computed in the C subsample; this one between the K criterion and the 12 predictor subtest scores taken as a set. Using the weights emerging from this exercise, a new Mechanical AI score (called C1M) was generated for all subjects in all cross-validation subsamples (A, G, E, and X as well as M). This completed the development of the C1M composite. The same procedure was repeated in the A, G, E, and X groups to generate C1A, C1G, C1E, and C1X for all subjects.

The procedure described in the previous two paragraphs was repeated, this time using the 12 subtest scores plus the 42 educational variables as the set of predictor variables. The prediction composites using all these predictors were designated as C2M, C2A, C2G, C2E, and C2X.

At this stage, three different sets of AIs, or predictor composites, were available for comparison in the cross-validation sample; namely, the four composites generated in the traditional way (M, A, G, and E), the five C1 composites generated using the K criterion and the subtest scores only (C1M, C1A, C1G, C1E, and C1X), and the five C2 composites generated against the K criterion using the subtest scores plus the

[1]In this study, the M, A, G, and E aptitude composites were recomputed and used in raw score (not percentile) form. Conversion problems with ASVAB 6 and 7 would not affect the results of the study.

educational variables (C2M, C2A, C2G, C2E, and C2X). Validity comparisons were made in the V subsample between the standard AIs and the C1 and C2 composites to determine whether or not the C1 and/or C2 composites improved prediction of final school grades in individual schools, and if so, how much improvement occurred.

III. RESULTS AND DISCUSSION

Validity coefficients against school grades were computed within each of the 119 schools. The uncorrected validities of the AIs, the C1 composites, and the C2 composites are shown in Table 2. The same validities, corrected for attenuation by selection (Guilford, 1950, formulae 13.29 and 13.31, p. 349) are shown in Table 3. The following observations are obvious from Table 3:

1. There is very little difference between the C1 and C2 composites. Validities averaged (using R to Fisher's Z transformation) across all schools were .59 for the C1 composites and .60 for the C2 composites. To improve validities by an average of only .01 is not worth using 42 additional predictor variables (the education variables). For the rest of this report, comparisons will be made only between the conventional AIs and the C1 composites.

2. There is worthwhile improvement, overall, in the predictive efficiency of the C1 composites as compared with AIs computed in the traditional manner. As mentioned in the previous paragraph, the overall average validity of the C1 composite, across all 119 schools, was .59. The average validity of the AIs across all schools was .50. It should be noted, however, that the improvement in prediction using the C1 composites may not be entirely attributable to the new way of computing the C1 composites, using the K criterion approach. There were at least two other differences between the formation of the traditional AIs and the C1 composites. First, all ASVAB subtests were used to form the C1 composites, whereas only selected subsets of subtest scores are used to form the traditional AIs. Second, the subtest scores comprising the AIs were unit weighted, whereas the C1 composite was formed by optimal weighting of all 12 subtest scores. Experience indicates that, in a cross-validation sample, optimal weights produce very little more prediction than unit weights and that, at least in most situations involving a large predictor set, only a very few variables have weights significantly different from zero. From a practical standpoint, the important fact is that composites computed in the manner of the C1 composites are more efficient in predicting success of airmen, for whatever reason. Still, it is important to understand more exactly why the C1 composites are superior to the AIs computed in the usual manner. A reanalysis of these data will be done to control for the variance which could possibly be introduced by optimal weighting and larger predictor sets in forming the C1 composites.

3. The validities of C1M, C1A, C1G, C1E, and C1X are all very similar, regardless of what is being predicted. For example, there is very little advantage in using the C1M composite to predict success in the mechanical area; C1A, C1G, C1E, and C1X all do about equally well. This is an interesting finding. It seems to argue that success in one area is similar to success in other areas. Also, differential prediction by tests of various "factors," which most researchers have been pursuing, may be, as McNemar suggests (McNemar, 1964), largely illusory. Certainly in this study, where no artificial controls were imposed on the selection and weighting of subtest scores, there is little to choose among the C1 M, A, G, and E composites, whatever one is predicting. Average validities of the various composites are given, by aptitude area, in Table 3.

Larger differences appear among the M, A, G, and E AIs computed in the traditional manner, although the selector composite is sometimes not the most efficient one; probably because, in the past, differences among the AIs were sometimes forced even though some overall validity was lost. Even these conventional AIs, formed in a theoretical framework rationally designed to maximize differential validity, are not generally very convincing in substantiating differential prediction as a practical goal of test construction.

Table 2. Comparison of Uncorrected Validities, Three Prediction Composites Against Technical School Final Grade[a, b]

School	Conventional Composites				C1 Composites					C2 Composites				
	M	A	G	E	M	A	G	E	X	M	A	G	E	X
M Schools														
114X0 (M50)	35	40	53	49	68	65	63	64	65	64	64	66	66	67
361X0 (M40)B[c]	23	22	26	31	41	34	39	41	40	47	43	46	46	48
361X1 (M40)B	32	28	30	23	40	37	39	37	38	46	40	41	39	45
423X1 (M40)B[c]	45	25	46	44	58	53	57	55	56	58	51	57	56	56
423X3 (M40)B	43	12	31	42	51	41	50	48	49	53	42	51	49	51
426X2 (M40)B	36	29	49	43	47	55	56	56	57	58	55	57	57	58
427X1 (M50)	30	31	45	34	52	51	50	50	52	53	52	50	51	53
427X3 (M40)B	34	24	41	28	48	47	48	45	47	48	45	49	45	47
427X4 (M40)B	17	30	20	18	36	37	39	33	37	39	37	42	35	39
427X5 (M40)B	37	04	22	40	44	34	43	43	42	46	35	43	44	43
431X0 (M50)	36	26	39	38	48	45	47	47	47	48	44	48	48	48
431X1 (M50)	32	28	40	40	53	49	52	51	52	53	47	52	51	52
431X2 (M50)	27	23	22	34	38	32	37	39	36	35	31	38	36	35
443X0 (M50)	38	29	39	43	49	45	48	50	49	50	44	48	50	48
472X0 (M40)B	57	16	34	49	38	30	38	40	36	40	27	38	39	35
472X1 (M40)B	43	15	32	41	50	42	48	47	48	51	43	49	48	51
472X2 (M40)B	38	12	39	36	48	40	47	44	45	48	41	46	44	44
531X3 (M40)B	14	12	36	33	33	36	29	35	35	31	33	28	33	32
531X4 (M50)	09	38	52	41	52	58	47	56	56	53	60	48	58	59
544X0 (M50)	55	21	07	44	57	37	56	55	52	58	28	54	54	55
546X0 (M50)	34	22	32	41	37	31	[illegible]	39	34	36	27	33	39	34
551X0 (M40)B	45	25	44	38	51	45	52	47	48	51	45	52	47	48
552X0 (M40)B	24	34	44	52	57	55	54	59	57	57	53	54	59	56
552X2 ([illegible]0)B	69	53	56	57	68	60	65	68	67	70	56	64	67	66
552X4 ([illegible]0)B	14	06	29	35	35	34	32	37	34	34	31	30	36	34
552X5 (M40)B	45	22	23	38	48	38	52	45	44	48	34	52	44	44
566X1 (M40)B	28	33	49	37	57	59	58	55	58	58	59	57	55	59
605X1 (M50)	22	33	46	35	50	53	51	50	51	51	52	52	50	51
A Schools														
207X1 (A60)	34	03	41	42	49	50	49	50	51	51	51	49	52	53
293X3 (A60)	33	32	46	40	52	50	52	49	51	53	52	54	50	52
554X0 (A60)	44	30	59	52	68	72	66	69	69	68	68	66	66	67
602X0 (A40)B	42	42	59	44	60	60	57	60	61	58	61	56	60	60
602X1 (A40)B	36	25	45	43	52	51	51	52	53	50	51	50	52	51
605X0 (A50)	20	09	45	44	42	51	39	48	48	44	53	41	48	51
645X2 (A70)	06	03	21	33	22	21	19	29	23	25	20	20	27	20
651X0 (A70)	36	24	63	45	57	62	55	57	60	57	62	55	58	60
672X1 (A80)	18	24	41	23	36	44	34	35	39	39	46	36	38	43
672X2 (A80)	29	24	50	37	48	54	48	48	51	47	54	48	49	51
702X0 (A40)B	22	23	39	30	40	44	39	41	43	40	43	39	41	42
732X0 (A60)	29	34	51	40	50	53	48	51	52	52	55	49	53	53
732X1 (A60)	38	05	62	51	60	60	56	60	61	57	61	57	59	61
G Schools														
[illegible]X0 (G80)	32	15	[illegible]		43	41	43	43	44	41	42	43	46	46
[illegible]0 (G60)	46	29	[illegible]		64	65	63	62	65	53	62	62	63	62
205X0 (G80)	31	07	4[illegible]		55	51	46	62	58	55	42	46	61	57
206X0 (G80)	28	38	37	35	43	44	41	45	45	39	39	40	44	42
231X1 (G60)	-06	34	27	-11	20	29	15	23	25	23	36	19	26	28
231X2 (G40)	42	[illegible]	54	51	66	65	68	65	68	67	66	70	67	71
233X0 (G60)	44	35	45	51	58	52	57	59	57	58	50	57	61	58
251X0 (G80)	35	13	35	39	48	47	47	47	50	49	43	48	48	50
274X0 (G60)	26	26	38	33	46	47	45	45	47	46	46	47	47	49
276X0 (G60)	30	17	42	35	49	51	49	48	51	51	51	51	48	53
291X0 (G60)	22	25	37	29	40	45	39	41	43	42	47	42	43	45
391X0 (G60)	28	21	61	34	57	67	56	56	63	56	66	58	58	65
427X2 (G50)	36	34	48	38	56	55	52	56	57	59	64	58	60	65
511X0 (G60)	27	19	40	35	42	45	39	43	44	42	42	39	44	44
511X1 (G60)	28	02	23	33	37	34	35	39	38	37	41	40	41	44
553X0 (G65)	55	37	51	68	61	55	57	66	62	61	54	58	67	62
571X0 (G40)	44	21	47	42	54	50	55	52	53	54	49	55	52	51
622X0 (G40)	19	18	37	22	37	43	36	35	40	38	44	36	36	40
622X1 (G60)	08	47	47	22	53	68	46	56	64	53	59	47	51	59
753X0 (G60)	26	24	44	27	50	45	50	43	46	51	48	48	41	48

Table 2 (Continued)

School	Conventional Composites M	A	G	E	C1 Composites M	A	G	E	X	C2 Composites M	A	G	E	X
G Schools (*Continued*)														
811X0 (G45)B	23	21	33	27	37	37	37	36	37	38	37	38	36	38
811X2 (G45)B	26	20	42	33	45	45	44	44	46	44	44	44	44	44
902X0 (G60)	29	32	49	35	48	52	47	47	50	49	53	48	48	51
902X2 (G60)	45	28	43	45	56	53	57	54	55	55	51	56	54	54
903X0 (G60)	46	37	46	54	61	57	59	62	60	60	55	58	61	60
904X0 (G60)	29	22	41	37	46	51	42	47	50	49	53	44	49	54
905X0 (G60)	38	44	47	49	59	62	57	61	62	58	65	59	63	65
906X0 (G60)	09	28	37	20	33	43	29	35	38	31	42	28	34	36
914X1 (G60)	30	43	48	28	44	49	42	41	46	43	52	42	41	46
915X0 (G60)	17	32	30	15	35	39	37	32	37	36	37	37	34	40
922X0 (G40)	28	41	45	27	49	50	49	46	49	49	52	50	47	50
981X0 (G60)	35	35	50	40	51	53	50	52	53	50	52	50	52	50
982X0 (G60)	26	19	32	27	40	43	40	40	42	40	48	41	42	44
E Schools														
275X0 (E60)	49	31	58	54	64	66	66	64	66	65	64	65	64	65
302X0 (E80)B	15	37	21	27	50	41	48	47	47	53	42	53	56	57
303X1 (E80)B	35	34	35	40	51	49	50	52	51	49	44	51	51	48
303X2 (E80)B	55	47	76	64	81	79	79	80	81	78	83	77	82	83
303X3 (E80)B	24	25	39	29	49	47	48	49	50	48	47	49	54	50
304X0 (E80)B	30	19	29	36	49	43	47	49	48	52	45	50	51	51
304X1 (E80)B	34	34	41	39	56	52	54	56	56	57	54	56	56	58
304X4 (E80)B	25	31	42	47	57	57	54	61	60	57	55	57	62	60
304X5 (E80)B	22	20	42	34	39	40	37	41	40	40	41	38	43	42
304X6 (E80)B	32	51	50	43	62	62	59	64	64	64	63	61	67	66
305X4 (E80)B	23	27	42	31	46	48	44	47	48	47	46	45	48	47
306X0 (E80)B	28	23	36	37	49	45	45	49	50	53	44	46	51	51
306X2 (E80)B	22	38	41	45	57	56	52	60	58	59	58	56	62	61
307X0 (E80)B	22	12	27	23	42	38	41	40	42	43	37	42	42	42
316X0 (E80)B	28	21	33	33	45	42	43	46	45	46	43	46	49	46
317X1 (E80)B	28	09	33	32	54	48	51	50	53	54	47	52	52	54
316X2 (E80)B	15	42	47	48	58	62	53	65	61	58	62	54	64	63
316X3 (E80)B	35	24	27	28	40	37	47	39	39	40	30	45	40	39
321X0 (E80)B	08	25	39	35	44	52	42	49	50	43	41	41	46	45
321X1 (E80)B	31	26	40	35	54	52	55	52	53	51	51	50	51	51
321X2 (E80)B	21	19	34	47	44	42	40	48	46	44	42	46	50	48
322X2 (E80)B	15	09	32	39	39	38	34	42	41	42	38	35	44	43
324X0 (E80)B	31	22	32	45	50	46	46	54	51	53	52	48	58	59
325X0 (E80)B	20	22	29	28	42	40	40	43	44	45	45	44	49	48
325X1 (E80)B	20	13	27	28	39	37	36	41	41	42	37	37	43	43
326X0 (E80)B	41	48	53	52	71	72	71	73	72	67	61	69	69	66
326X1 (E80)B	24	18	34	34	43	42	39	45	45	42	38	39	44	44
326X2 (E80)B	37	16	26	35	47	36	49	44	44	51	41	53	48	49
328X0 (E80)B	22	19	28	32	45	40	44	45	45	46	38	44	48	46
328X1 (E80)B	25	29	39	41	53	51	48	56	55	53	47	49	58	55
328X3 (E80)B	37	22	39	48	58	54	55	60	60	60	56	56	63	62
328X4 (E80)B	20	23	40	40	49	49	46	54	52	51	49	47	57	54
341X4 (E80)B	31	06	-13	32	39	19	33	40	40	46	26	36	49	48
341X6 (E80)B	24	42	31	39	47	44	44	51	48	52	45	46	55	55
362X1 (E60)	31	18	32	35	48	41	45	48	47	46	38	44	46	45
362X2 (E60)	20	56	57	52	57	65	55	62	62	60	62	57	63	63
362X4 (E60)	42	27	58	43	68	63	67	66	67	67	60	66	66	66
403X0 (E80)B	29	28	50	51	61	59	57	64	62	60	43	57	62	57
404X0 (E60)	57	53	48	58	65	56	65	65	61	66	57	68	64	63
404X1 (E60)	16	14	49	13	44	33	48	31	36	42	34	47	32	35
423X0 (E50)	34	19	43	43	52	51	50	54	53	54	51	52	56	56
463X0 (E60)	44	43	59	49	64	62	62	65	65	62	58	62	63	62
541X0 (E50)	46	40	46	49	61	56	60	60	60	62	57	61	60	60
542X0 (E50)	71	22	45	67	75	60	74	74	71	77	64	75	75	75
542X1 (E50)	40	46	55	48	61	60	61	61	60	64	66	65	64	66

[a]Selector AI for each school in Bold.
[b]Decimal points have been omitted from correlations to save space.
[c]"B" designates Base schools. All others are Target schools.

Table 3. Comparison of Corrected Validities, Three Prediction Composites Against Technical School Final Grade[a, b]

School	Conventional Composites M	A	G	E	C1 Composites M	A	G	E	X	C2 Composites M	A	G	E	X	N
M Schools															
114X0 (M50)	44	42	57	55	67	68	67	68	69	68	68	69	70	70	148
361X0 (M40)B[c]	30	21	28	35	44	37	43	45	44	50	46	49	49	51	54
361X1 (M40)B	43	34	40	34	49	46	48	46	47	54	48	50	48	53	59
423X1 (M40)B	52	25	50	50	62	57	61	60	61	63	55	61	60	60	311
423X3 (M40)B	49	12	34	48	56	44	55	53	53	57	46	56	53	55	280
426X2 (M40)B	40	28	50	46	59	57	58	58	59	60	56	59	59	60	1,700
427X2 (M50)	39	31	49	41	56	55	55	55	56	57	55	54	55	57	262
427X3 (M40)B	40	25	45	35	52	51	52	49	51	52	48	53	49	52	141
427X4 (M40)B	22	32	22	22	38	39	40	36	39	40	39	43	37	41	148
427X5 (M40)B	41	04	25	44	48	37	46	47	45	49	37	47	47	46	341
431X0 (M50)	45	27	44	46	54	50	54	53	53	54	50	54	54	54	209
431X1 (M50)	39	29	44	45	56	52	56	55	56	57	50	56	54	55	2,295
431X2 (M50)	35	25	27	40	44	37	42	45	42	42	35	44	42	41	67
443X0 (M50)	48	32	46	51	56	51	55	56	56	57	50	56	57	55	322
472X0 (M40)B	73	25	52	66	60	50	60	60	57	61	46	59	59	56	48
472X1 (M40)B	52	17	38	49	57	48	55	55	55	58	49	56	55	57	173
472X2 (M40)B	41	12	40	38	50	42	49	46	47	49	43	48	45	46	165
531X3 (M40)B	15	13	36	33	33	36	29	35	35	31	33	28	33	32	102
531X4 (M50)	11	38	52	40	50	57	45	54	55	51	59	46	56	58	48
544X0 (M50)	68	27	09	56	69	46	68	66	64	69	34	67	65	65	28
546X0 (M50)	46	27	39	50	47	40	46	48	45	47	36	45	48	45	99
551X0 (M40)B	55	27	51	48	59	52	60	55	56	59	52	59	55	56	207
552X0 (M40)B	29	35	45	54	58	57	56	61	59	58	54	55	61	58	142
552X2 (M40)B	80	64	67	71	79	71	76	79	78	80	66	76	78	77	44
552X4 (M40)B	19	07	31	37	[illegible]7	35	34	39	36	36	33	32	38	36	49
552X5 (M40)B	55	16	27	47	[illegible]7	44	60	54	52	57	40	60	53	52	129
566X1 (M40)B	36	35	53	43	[illegible]0	62	61	58	61	61	61	60	58	62	200
605X1 (M50)	33	34	51	42	[illegible]4	57	54	54	55	55	56	56	54	55	558
Totals and Averages	44	27	42	46	55	[illegible]	54	54	54	56					8,229
A Schools															
207X1 (A60)	34	04	41	32	49	49	48	50	51	51	50	49	52	53	227
293X3 (A60)	39	38	49	42	55	53	55	52	54	55	54	57	52	55	198
554X0 (A60)	44	65	60	52	69	73	68	70	71	69	69	67	67	69	49
602X0 (A40)B	43	46	61	46	62	63	60	63	63	60	64	59	62	62	149
602X1 (A40)B	37	31	48	44	54	53	54	55	55	52	53	52	54	53	135
605X0 (A50)	21	11	45	45	42	50	39	47	47	44	53	41	47	50	112
645X2 (A70)	05	04	20	33	22	20	19	28	23	25	19	20	27	20	30
651X0 (A70)	38	33	65	47	60	63	58	60	63	61	65	58	61	63	72
672X1 (A80)	20	37	49	28	43	51	42	42	46	45	58	43	45	50	244
672X2 (A80)	33	40	57	45	55	60	55	56	57	54	60	55	56	57	357
702X0 (A40)B	23	26	41	31	42	45	40	42	44	42	45	40	43	44	3,345
732X0 (A60)	31	43	56	44	55	38	53	56	57	56	60	54	58	58	623
732X1 (A60)	38	06	61	51	60	59	56	60	61	57	61	57	58	60	27
Totals and Averages	32	28	51	42	52	55	51	53	54		55				5,568
G Schools															
202X0 (G80)	46	30	55	45	59	59	59	59	60	58	59	59	61	61	59
204X0 (G60)	53	37	69	53	72	72	70	70	72	70	70	70	70	69	83
205X0 (G80)	39	38	70	67	74	73	68	78	76	73	68	68	77	75	43
206X0 (G80)	53	58	64	61	66	66	65	67	67	63	64	64	67	65	88
231X1 (G60)	-03	37	32	15	25	33	20	27	30	28	39	24	30	32	59
231X2 (G40)	39	21	50	47	63	63	65	62	65	64	64	68	64	69	44
233X0 (G60)	48	42	52	56	63	58	62	64	62	63	56	62	66	62	101
251X0 (G80)	46	32	55	55	62	61	61	62	63	62	59	62	62	64	185
274X0 (G60)	33	32	45	40	51	52	51	51	52	52	51	52	52	53	111
276X0 (G60)	36	26	50	43	56	58	56	55	57	57	58	58	55	59	433
291X0 (G60)	29	31	46	37	48	51	47	49	50	50	53	49	50	52	590
391X0 (G60)	36	29	69	44	65	73	64	64	70	64	72	66	66	71	59
427X2 (G50)	38	37	51	41	[illegible]8	58	55	59	60	62	66	60	63	67	77
511X0 (G60)	36	28	51	45	5[illegible]	55	50	53	54	52	52	49	53	53	336
511X1 (G60)	37	11	37	43	40	44	45	47	47	46	49	48	40	51	55
553X0 (G65)	66	52	65	75	71	[illegible]	69	74	72	71	67	69	75	72	60
571X0 (G40)	44	21	47	42	51	50	55	51	53	54	40	54	52	51	909
622X0 (G40)	22	21	40	[illegible]	40	45	39	38	42	41	46	39	39	43	368
622X1 (G60)	18	58	66	[illegible]	64	78	62	70	76	68	72	63	67	72	38
753X0 (G60)	25	33	53	[illegible]	56	53	56	51	54	57	55	53	49	55	35

Table 3 (*Continued*)

School	Conventional Composites M	A	G	E	C1 Composites M	A	G	E	X	C2 Composites M	A	G	E	X	N
G Schools (*Continued*)															
811X0 (G45)B	24	22	35	28	38	38	38	37	38	39	38	39	37	39	5,917
811X2 (G45)B	27	22	44	35	47	47	46	46	47	46	46	45	46	46	1,218
902X0 (G60)	35	39	56	43	54	58	53	54	56	55	59	54	55	57	1,192
902X2 (G60)	49	35	50	56	61	58	61	59	60	60	57	61	59	59	130
903X0 (G60)	50	41	52	59	65	61	63	65	64	64	60	62	64	64	92
904X0 (G60)	34	27	47	43	51	55	47	52	55	53	57	49	54	58	231
905X0 (G60)	45	51	55	56	64	67	63	66	67	64	69	64	68	69	113
906X0 (G60)	16	33	45	28	41	49	37	42	45	39	49	37	42	44	202
914X1 (G60)	36	48	54	35	50	54	49	47	52	49	58	48	48	52	53
915X0 (G60)	21	37	36	21	40	43	41	38	41	41	42	42	39	44	152
922X0 (G40)	28	41	45	26	48	50	49	46	49	49	51	50	47	50	353
981X0 (G60)	46	44	61	50	61	64	60	62	63	61	62	60	62	61	185
982X0 (G60)	31	24	39	33	45	48	45	45	47	46	52	46	47	49	98
Totals and Averages	36	35	52	44	56	57	55	56	58			55			13,772
E Schools															
275X0 (E60)	52	33	60	57	66	68	68	66	68	67	66	67	66	67	82
302X0 (E80)B	22	47	37	43	58	51	57	56	56	61	51	61	62	64	31
303X1 (E80)B	51	38	49	57	63	61	63	65	64	62	57	64	64	61	92
303X2 (E80)B	65	60	83	75	86	85	85	86	87	84	88	83	87	88	36
303X3 (E80)B	42	36	53	49	61	59	60	66	61	60	59	61	63	67	143
304X0 (E80)B	48	29	46	58	62	58	61	62	62	64	58	63	63	63	322
304X1 (E80)B	50	46	55	56	67	64	65	67	67	67	65	67	67	68	121
304X4 (E80)B	45	38	56	66	71	69	69	73	73	71	68	71	74	73	417
304X5 (E80)B	45	38	58	57	58	58	56	60	59	59	58	57	61	60	72
304X6 (E80)B	50	60	66	64	74	74	72	75	75	75	74	73	77	76	68
[illegible]X4 (E80)B	35	33	50	43	54	56	52	54	56	55	54	53	55	55	237
306X0 (E80)B	44	27	50	54	61	58	58	61	62	64	57	59	62	63	115
306X2 (E80)B	44	49	56	63	69	68	66	72	70	71	69	69	73	72	85
307X0 (E80)B	36	14	38	40	52	49	51	50	52	52	47	52	51	52	159
316X0 (E80)B	43	32	47	50	57	55	56	57	57	58	55	57	59	58	230
317X1 (E80)B	42	12	46	49	63	58	61	60	63	63	57	62	62	63	146
316X2 (E80)B	38	47	62	67	73	75	69	77	75	72	74	70	76	76	43
316X3 (E80)B	44	29	38	40	48	45	54	47	48	49	39	52	48	48	29
321X0 (E80)B	27	25	53	53	57	62	55	61	61	56	54	55	59	58	93
321X1 (E80)B	52	38	56	56	66	65	67	65	66	65	64	64	64	64	61
321X2 (E80)B	41	26	53	65	63	60	59	66	64	63	59	63	67	65	245
322X2 (E80)B	37	24	54	61	60	58	56	62	61	61	58	57	63	62	117
324X0 (E80)B	51	30	43	62	65	60	61	68	68	67	63	63	70	71	99
325X0 (E80)B	39	27	43	48	56	53	54	56	57	58	57	57	60	60	211
325X1 (E80)B	33	14	36	41	49	46	46	49	50	50	46	46	51	51	319
326X0 (E80)B	63	48	66	71	82	82	82	83	83	79	74	80	80	79	36
326X1 (E80)B	42	21	47	52	57	55	54	58	59	56	52	54	58	57	264
326X2 (E80)B	57	26	46	59	65	55	65	68	63	67	59	68	66	66	127
328X0 (E80)B	37	30	42	48	56	52	55	56	56	57	50	55	59	57	236
328X1 (E80)B	44	37	53	60	66	63	62	68	68	66	59	63	69	67	342
328X3 (E80)B	53	29	53	65	70	66	68	72	71	71	67	68	74	73	317
328X4 (E80)B	38	27	52	57	62	60	59	65	64	63	59	60	67	65	247
341X4 (E80)B	55	17	2	57	60	44	56	60	60	63	47	57	65	65	33
341X6 (E80)B	50	57	54	63	67	64	65	69	67	69	63	66	71	71	32
362X1 (E60)	42	24	41	46	56	50	54	55	55	54	47	53	55	53	122
362X2 (E60)	32	62	65	61	65	71	63	69	69	67	68	65	70	70	50
362X4 (E60)	48	29	62	59	71	67	70	69	70	71	64	69	69	69	91
403X0 (E80)B	58	46	65	73	77	75	75	79	78	77	61	75	78	75	27
404X0 (E60)	61	55	53	62	69	60	68	68	65	70	61	71	68	67	10
404X1 (E60)	46	15	50	18	44	35	47	32	37	42	36	46	33	36	36
423X0 (E50)	45	23	52	54	61	59	58	63	62	62	58	60	64	64	155
463X0 (E60)	56	52	68	63	73	71	71	73	74	72	68	71	72	71	115
541X0 (E50)	52	43	51	55	65	61	65	65	64	66	61	66	64	64	291
542X0 (E50)	79	31	59	77	82	71	81	81	79	83	74	82	83	82	76
542X1 (E50)	40	52	62	57	67	66	67	67	67	70	71	70	70	71	104
Totals and Averages	47	35	53	57	65	62	63	65	65				67		6,645

Overall Totals and Averages Selector AIs Only

Only	AI = 50	C1 = 59	C2 = 60	31,211

[a]Selector AI for each school in Bold.
[b]Decimal points have been omitted from correlations to save space.
[c]"B" designates Base schools. All others are Target schools.

When individual aptitude areas, individual levels, and individual schools are considered, the K criterion technique finds even more utility. The average of C1 composite validities for M schools is .55; the average conventional M aptitude index is .44 (see Table 3). C1A averages .55 for A schools, whereas the average AI-A is only .28. The average C1G (for G schools) is .55, while the average AI-G is .52. Finally, the average C1E is .65, compared with an average AI-E of .57. Certainly in the M and A areas, the C1 composites are superior to the AI composites. In the G area, the C1 composite is slightly better than the AI, and in the Electronic area, the difference is well worthwhile.

The largest improvement is obviously in the A schools, and a close scrutiny explains why. Of the 13 A schools, the AI-A composite yields the *least* prediction of all the conventional AI composites in nine of them (69%). In fact, in every one of the A schools, the conventional AI-G appears to be a better predictor than AI-A. In no other aptitude area is this true. Taking into account that the A schools comprise 11,143 subjects (a very large sample), the development of a new Administrative composite would seem to be worthwhile, even if the AIs continue to be computed in the conventional way.

Considering levels within aptitude areas, the Base groups (that group in which the weights were derived which were then applied to the target groups) would be expected to produce higher C1 validities than the Target groups because the equations that were instrumental in producing the K criterion were derived in the Base groups. If the C1 validities of the Base group are substantially higher than those of the Target groups, more benefit would be expected from using the C1 composite with schools at that level. However, the evidence argues the opposite case.

In the M area, the average AI-M validity for the Base schools is .45 and the average C1-M validity for these schools is .54, an increase of .09. In the Target schools (see Table 4), the average AI-M validity is .41 and the average C1-M is .56, an increase of .15.

Table 4. **Improvements in Prediction by C2 Composites, Base and Target Schools Compared**

	Base Schools	Target Schools
AI(M)	.45	.41
C1(M)	.54	.56
Difference	.09	.15
AI(A)	.35	.25
C1(A)	.54	.55
Difference	.19	.30
AI(G)	.40	.52
C1(G)	.42	.55
Difference	.02	.03
AI(E)	.57	.56
C1(E)	.65	.66
Difference	.08	.10

In the A area, the average AI-A validity is .35 for Base group schools and average C1-A validity is .54, a difference of .19. In the A area Target schools, the average AI-A validity is .25 and average C1-A validity is .55.

G-area Base schools produce an average AI-G validity of .40 and average C1-G validity of .42, an improvement of only .02. The Target schools produce an AI-G validity of .52 and a C1-G average validity of .55, an improvement of .03.

Overall, the average AI-E validity in the Base groups is .57, which increases to .65 (a .08 improvement) when the C1-E composite is used. In the E area Target schools, the average AI-E validity is .56, compared with .66 for the C1-E composite, an improvement of .10.

In summary, the C1 composite produces more improvement in the Target schools in every instance (though the effect is small in the G area). This result is exactly the opposite of predictions, and the reason this effect should appear is unknown. At any rate, using the C1 composites in the Target schools (rather than the AI composites) would be more advantageous than using them in the Base schools.

There were very large differences among individual schools in the amount of predictive improvement effected by the C1 composite. These differences ranged from -.12 (school 231X1, G60) to +.53 (school 732X1, A60). There was no increase in predictive accuracy in only 12 of the 119 schools. The validities of 45 schools improved at least .10 when the C1 composite is substituted for the traditional AI composites, 24 schools improved at least .15, and 12 improved at least .20. Clearly, there are many individual schools in which use of the C1 composite could result in substantial improvement in predictive efficiency.

IV. CONCLUSIONS AND RECOMMENDATIONS

The information contained in this report leads to the following conclusions and recommendations:

1. Across all schools, the method of producing the C1 composite yields results substantially better than the traditional method of producing the AI composite. The traditional approach produces an average validity of .50, compared with .59 produced by the C1 composites. The difference between the squares of these validity coefficients is .10 (.35 minus .25), and the proportional improvement (.10 ÷ .25) is .40. This last number means that, starting with 25% predictive efficiency using the conventional AIs, a 40% improvement (raising 25% up to 35%) can be made by forming the AIs in the manner described for the C1 composites. If C1 composites are used to select for some but not all the schools, much more dramatic results may be obtained (e.g., 114X0, 531X4, 552X0, 566X1, 605X1, all the A schools, 362X4, and others). Using AIs computed in the traditional manner to select for some schools, and C1 composites computed as in this study to select for others is not a serious problem. The only additional procedure involved would be the computation and recording for each enlistee of an additional set of composites—an almost trivial procedure for a computer.

2. The C1 composites are not substantially improved by adding educational variables to the set of subtest predictors.

3. Although the primary objective of this study was not the evaluation of the predictive efficiency of the conventional aptitude indexes, the Administrative AI, as currently constituted, shows up as such a poor selector for schools in the Administrative area that this finding should be documented. Ascertaining the validity of this finding should be the objective of future research on ASVAB composites and if confirmed, efforts should be directed to the development of a new Administrative AI to increase the predictive validity of this composite.

4. The K-composite procedure worked rather well. It is a procedure which should be useful not only in the context described herein, but also in academic prediction studies involving grade point averages of freshmen, sophomores, juniors and seniors collapsed into a single criterion group. The procedure could also be used in studies predicting rating criteria collected on the same scale on subjects of different ranks and in other situations where criterion data are collected across groups of varying levels on scales restricted by arbitrary upper or lower limits.

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