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Examining Training Eligibility Standards: Four Case Studies

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14. ABSTRACT *(Maximum 200 words)*: The objective of the study was to examine the feasibility of putting the determination of MOS training eligibility standards (i.e., AA composite cutoff score levels) on firmer empirical footing. The key to establishing defensible cutoff levels is the estimation of empirical relationships between student training performance and AA composite scores. Accordingly, the authors estimated training performance relationships and utilized the estimated parameters to examine the impact upon training performance of changes in training eligibility standards, with the aim of identifying defensible standards.

The authors specified and estimated binary logistic models based on course-level pass / fail data and regression models using overall student average data for four MOS. These criteria or dependent variables were estimated as functions of AA governing composites and Soldier demographic variables. The authors found moderate correlations between student performance and AA composites, and relatively modest explanatory power of the estimated logistic and OLS regression models.

The four MOS also illustrated the difficulties of the intended exploration. Advanced Individual Training (AIT) is closely managed; with the data available it is not always possible to distinguish the better from the poorer students. In particular, it is difficult to accurately distinguish between failure to complete training due to academic versus non-academic reasons; there is not much variation in student training performance scores; and there would appear to be a lot of ongoing student remediation.

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EXAMINING TRAINING ELIGIBILITY STANDARDS: FOUR CASE STUDIES

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Introduction

Background

The Armed Services Vocational Aptitude Battery (ASVAB) is a battery of tests taken by prospective applicants to determine mental eligibility for military service and job training. In the Army, these tests are combined to form Aptitude Area (AA) composites to determine individual qualification for particular job training opportunities.

There are nine composites and they correspond to the existing nine Army job families. Military Occupational Specialty (MOS) membership in job families reflects historical use and earlier classification analyses. In classification, each AA composite becomes the "governing" composite for all MOS in the corresponding job family; to utilize the governing composite, the school proponent in conjunction with Enlisted Accessions Division (of the Deputy Chief of Staff for Personnel) and the Human Resources Command (HRC) set a cutoff level or minimum standard for job training eligibility. At one time the cutoff level was based on findings from training performance research; over the years the cutoff level has occasionally been adjusted by school proponents but there has been no requirement for periodic review of this level. In the adoption of least-squares weighted composites (see below) and the establishment of revised cutoff levels, ARI examined the percentage qualifying under different cutoff levels in an attempt to keep that percentage roughly the same as under the old (unit-weighted) composite standards.

The recent decision by DOD to delete the two "speeded tests" – Coding Speed and Numerical Operations – in the ASVAB necessitated that the Army reconfigure its composites. In response, the adoption of least-squares weighted composites took effect in January 2002. These composites are defined for the same nine Army job families but are empirically more defensible than the composites they replaced because job performance was utilized as a criterion in their estimation and a more sophisticated approach to combining ASVAB tests for classification purposes was followed. The overall effect is to yield improved congruence between test composites and job performance and to make possible a more powerful system of classifying Soldiers into jobs.

Objective of the Study

The objective of this study was to examine the feasibility of putting the determination of cutoff levels on firmer empirical footing. The key to establishing defensible cutoff levels is the estimation of empirical relationships between student training performance and AA composite scores. Accordingly, we have estimated training performance relationships and utilized the estimated parameters to examine the impact upon training performance of changes in training eligibility standards, with the aim of identifying defensible standards.

Our research is related to a recent study prepared for the ARI by Diaz, Ingerick, Fowler and Lightfoot (2004). That study used a large amount of computer generated data to provide guidance on training policy issues, including the link between AA composite scores and academic attrition rates. They simulated their data to reflect key characteristics of a single MOS. While such simulation studies are quite useful and have many advantages, they can also neglect circumstances that differ between MOS families that could be important to consider when making recommendations for changes to the policies of a particular MOS proponent. Consequently, in this research we provide analysis of data from several different MOS, and in this way provide a complement to previous simulation based research.

We have acquired training performance data from the Automated Instructional Management System (AIMS), managed by the Army Training Support Center (ATSC), Fort Eustis, VA. The data reflects 1999 – 2000 AIT experiences of approximately 8016 Soldiers in MOS 14E (Patriot fire control operator/ maintainer), 55B (ammunition specialist), 55D (explosive ordnance disposal specialist), and 77F (petroleum supply specialist).

Note that the pre-2002 AA composites were in effect during this period, so that the particular results we report are subject to revision. The focus of the reader, therefore, should be on the methodology rather than the results per se. The longer term objective is development of a handbook that can be applied by school proponent analysts to conduct similar types of analysis or by ARI researchers as part of an ongoing service to school proponents.

Data

Data Sources

ATSC provided ARI with a special extract from the AIMS system of individual training performance records for students in four MOS's (14E, 55B, 55D, and 77F). As shown in Table 1, the records provided information on age,

Table 1.
Data requested from the AIMS system.

Field description
Person identifier
Person's Name (Last, First)
Person rank
Age as of class end date
Gender
Martial Status as of class end date.
Lang Code
Lang Proficiency
Race
Organization unit type
Education
Fiscal Year course is taught in
Military School Code
Course Delivery Group
Course Phase
Class Identifier
Section Identifier
Class Start Date (YYMMDD)
Class End Date (YYMMDD)
Class standing
Number of students in class
Section standing
Number of students in section
Student Average (POI percentage points)
Input Status
Output Status
Reason code (ATSC combination code)
Test #1: Name
Test #1 score: percentage score (x100)
Test #1: order of test results (if test taken more than once)
Test #1: computed POI points from the test
Test #1: highest number of POI points possible
...
...
Test #32 Name, etc

gender, training dates, input status, output status, and test scores. Composite scores, education and other demographic information were obtained from the Enlisted Master File (EMF).

Data Editing

Tests Blocks. Courses are organized into instruction blocks, which contain material pertaining to specific skill areas that students are required to master before moving on to the next block. The process of instruction and assessment within the blocks involves presentation of the material followed by testing. Students who receive a failing score are immediately retrained and retested. For those who pass the test the second time, the lowest possible passing score is recorded. Those who fail the retest are generally removed from the course and either recycled into another class in the same course or retrained in a different MOS.

Data on five variables from each instruction block are recorded. These data include the name of the test; how many times the student took the test in order to pass (order); the number of points the student earned on the test (points); the possible number of points a student could earn on the test (POI)[1]; and the student's percentage score, calculated by dividing the number of points earned by the number of possible points (score).

Each student's course average had been calculated in the original data provided. Apparently, the total number of points was divided by the total POI for the course then multiplied by 100. In several cases, individuals were listed as earning a zero on more than one test. These were edited to eliminate all but one zero, because Army rules would prevent a student from earning a failing grade on more than one test. After this adjustment, a Student Average was re-calculated for each participant by summing the total points earned and dividing by the number of possible points (POI) in the tests that the participant had taken. This process produced some scores far enough below the mean to be suspect. Upon inspection it was determined that these records contained more than one non-zero failing grade. These data could not be verified as accurately recorded, so these participants were dropped from further analysis.

Status Variables. Participants received an input status code that describes their status upon entry into the course (e.g. new input or recycled in from another class in the same course), and an output status code that describes their status upon leaving the course (e.g. graduated; retrainee out into another course of instruction). Input and output status were further explained by a variable describing the reason for the student's code (see Appendix B). Student output status and reason for that status were used to create a new variable listing each student's outcome in the course. Four codes were used for the new

[1]Results for each instruction block were not provided in any particular order. Upon request, each school provided a list of the order in which its tests were administered. Once these were received, frequencies were printed for each variable. New variables were created for each instruction block in the order the school provided.

output variable: graduated, did not graduate for academic reasons, did not graduate for non-academic reasons, and no output information available.

ASVAB. The AIMS system could not provide scores for the AA composites (calculated from the ASVAB subtests). They were obtained with the assistance of HRC staff from the EMF. See Appendix A for a description of the AA composites in effect before and after January 2002.

Demographic Information. Education information (obtained from the EMF) had been entered as two mutually exclusive variables. These were combined and collapsed into three categories: Earned a General Education Development or did not finish high school (GED), earned a high school diploma (High School), and attended some college (College).

Information pertaining to race and ethnicity were found in several variables, of which REDCAT2 was the most similar to the accepted racial classification in psychology (i.e. White, African American, Hispanic, Asian/Pacific Islander, Other; APA 2001). REDCAT2 was recoded into two categories: White and Minority.

Several students were recorded as less than 17 years old. These ages were recoded as missing data because individuals under the age of 17 cannot join the US Army.

Method

Participants

The sample included individuals who had completed Advanced Individual Training (AIT) for the MOS described below, individuals who had failed to complete the course for academic reasons, and individuals who had started the course but whose class was still in session. For students who were still in a class, Student Average was calculated for the instructional blocks they had completed. Demographic data are presented in Table 2.

Analysis Plan and Model Specification

As described earlier, we sought to examine the impact of training eligibility standards upon training attrition and training performance. And to simplify the task, we focused on "academics" and attempted to exclude those Soldiers categorized as non-academic attrition from the classroom (because we lacked the requisite information to predict this).

When examining the impact upon training attrition, we used the logistic regression model to explain the Soldier's pass / fail training outcome as a function of Aptitude Area (AA) scores. The relationship between Soldier attrition probability P(X) and AA score that is equal to X can be stated as

$$P(X) = e^{(a+\beta X)} / (1+e^{(a+\beta X)}),$$

Table 2.

MOS	*14E*	*55B*	*55D*	*77F*
Number of Students	570	148	84	3285
Gender	Male = 88.5% Female = 11.5%	Male = 78.3% Female = 21.7%	Male = 92% Female = 12%	Male = 72.3% Female = 27.7%
Race	White = 70.7% Other = 29.3%	White = 65.3% Other = 34.7%	White = 90.8% Other = 9.2%	White = 39.2% Other = 60.8%
Education Level	GED = 10.5% HS Dipl. = 82.6% College = 6.9%	GED = 12.8% HS Dipl. = 85.1% College = 2%	GED = 3.4% HS Dipl. = 86.2% College = 10.3%	GED = 8.5% HS Dipl. = 85.9% College = 5.6%
Output Status	Grad = 56.1% Non-grad = 6.4% Class in prog=37.5%	Grad = 68.4% Non-grad = 0% Class in prog=31.6%	Grad = 32.4% Non-grad =13.7% Class in prog=53.9%	Grad = 83.3% Non-grad = .2% Class in prog=16.5%
Mean Age	M = 22.5 SD = 4.2	-	M = 22.7 SD = 4.7	M = 21.2 SD = 3.6
Mean Student Average	M = 86.9 SD = 12.5	M = 92.8 SD = 3.8	M = 87.9 SD = 9.6	M = 88.4 SD = 7.1
Mean Score Governing AA Composite	*MM* M = 114.0 SD = 7.3	*ST* M = 107.7 SD = 7.6	*GM* M = 119.1 SD = 8.3	*CL* M = 101.0, SD = 9.5 *OF* M = 99.7, SD = 9.1
Passing Score	*70*	*70*	*85*	*70*

where a and β are estimated parameters. The probability function P(X) is non-linear, defined between zero and one, and inversely related to the AA score.[2] Note that the β parameter of the model is not the marginal effect of a change-in-X upon the probability. In this model, the marginal effect evaluated at X=x is given by the product of β, P(x), and 1-P(x).

When the MOS-specific training data contained too few observations of (academic) attrition with which to conduct an attrition analysis, we examined the relationship between training performance and AA score, and inferred the impact of changes in AA cut scores upon pass / fail rates via the impact upon student scores. We specified an ordinary least squares (OLS) regression of the form

$$Y_i = X_i' \beta + e_i,$$

where the Y_i is the i-th Soldier's score, X_i represents the set of explanatory variables, AA_i and one or more demographic control variables, β is a coefficient vector and e_i is the disturbance term. The OLS estimates of β have desirable properties (unbiasedness, consistency, efficiency and asymptotic normality) under standard regularity conditions

[2] This model is described in some detail in a training attrition context by Diaz, Ingerick, Fowler, and Lightfoot [2004].

including that the known explanatory variables are uncorrelated with the disturbance term, which represents unknown factors and random effects. In the case at hand – of selection into the Army and assignment into job specific training, there is likely to be some degree of self-selection bias inasmuch as the disturbance term reflects the Soldier's intrinsic ability in the specific MOS and this is likely related to the Soldier's test taking skills and a determinant of his / her AA score. However, because the selection and assignment is sequential and over multiple alternatives, accounting for this potential selection bias is computationally extremely cumbersome and sensitive to specifics regarding the way in which the selection problem is modeled. Moreover, perhaps because of the relatively small samples associated with most of our MOS data, our preliminary efforts at correcting for this bias had very little impact on our substantive conclusions. As a result, we report below our findings from models that assume the standard regularity conditions hold.

We also have occasion to estimate a censored regression model – the Tobit model.[3] In the training context, when we see a relatively large number of student scores clustered at 100, the maximum score obtainable, we do not see the full potential range of scores. It is as if the "potential" scores are all transformed to (or reported as) a single value of 100. In this case special estimation methods are called for to account for the degree of censoring observed in the data.

To be precise, let Y_i represent the test score that is actually observed, which cannot exceed 100. Then, let Y_i^* be the true score that a student is capable of attaining, if he / she were able to earn scores above 100. Loosely speaking, one way to think about this is that some students might be so excellently prepared that they could earn 20 additional extra credit points, if those points were available. At the same time, other students would only be able to earn a few of those points. Then the idea is that the Y_i observed is equal to the actual score Y_i^* whenever Y_i^* does not exceed 100, but Y_i is equal to 100 whenever Y_i^* is greater than 100.

Writing this same idea out more formally, we have that the unobservable variable is determined by $Y_i^* = X_i^{\prime}\beta + e_i$ where X_i is again a set of explanatory variables, β the associated coefficient vector and e_i a noise term that is assumed to follow independent and identical Gaussian distributions across all i. The observed variable is then determined by the following:

$$Y_i = \begin{cases} Y_i^* \text{ if } X_i^{\prime}\beta + e_i \leq 100 \\ 100 \text{ otherwise} \end{cases}$$

This model cannot be estimated using standard Ordinary Least Squares procedures. Instead one must base inferences on the log likelihood function associated with this

[3] Refer to Greene, pp. 691-694.

model.[4] Although this is nontrivial, many statistical software packages are available for this purpose.

Data editing was completed using the SPSS version 11.05 (2003), which was also used to calculate frequencies and estimate stepwise regression models. LIMDEP 7.0 (1995) and LIMDEP 8.0 (2002) were used to estimate binary logistic, OLS, and censored regression models.

Data Analysis and Results

14E: Patriot fire control operator / maintainer[5]

Results. Descriptive statistics are reported in Table 3. The final sample of 587 Soldiers consisted of those who had passed the course or failed to complete the course for academic reasons, and had met the cut score of 105 (or the "waiverable" score of 102) on the governing AA composite, Mechanical Maintence (MM). The mean for Student Average was 86.9, with a standard deviation of 12.5.

Table 3.
14E: Means table for composites and Student Average

Variable	Mean	Standard Deviation	Minimum	Maximum
Student Average	**86.9**	**12.5**	**7.5**	**100**
CL	112.4	10.7	85	133
CO	114.4	9.5	89	138
EL	112.4	10.4	83	139
FA	114.7	11.2	85	142
GM	111.9	9.1	84	138
MM	114.0	7.3	102	136
OF	114.2	7.3	95	134
SC	113.4	9.1	86	136
ST	113.9	9.9	88	135
GT	112.0	10.1	81	131

As shown in Table 4, AA composites are moderately to highly correlated. Student Average was most highly correlated with the Field Artillery (FA) composite and least correlated with MM, the governing AA composite. There are (at least) two possible explanations for why the governing AA composite score is the least correlated with Student Average: first, this could be a reflection of the restricted range of the governing composite; and second, it is possible that MM does not measure the ideal skill set for success in MOS 14E.

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[4] It can be shown that the log likelihood function is given by the following equation:

$$L = -\frac{1}{2}\sum_{i:Y_i<100}\left\{\left(\frac{Y_i - X_i'\beta}{\sigma}\right)^2 + \log 2\pi\sigma^2\right\} + \sum_{i:Y_i=100}\log\left\{1-\Phi\left(\frac{100-X_i'\beta}{\sigma}\right)\right\}$$ where Φ is the cumulative distribution function for a standard normal random variable, and log represents the natural logarithm.

[5] The Military Occupational Classification and Organizational Structure pamphlet (611-211) describes the duties of a skill level one 14E graduate as "performing march order and emplacement of the fire control system (FCS), fire distribution system (FDS), and associated equipment; initializing and operating different targeting and communications equipment; performing organizational level systems maintenance and preventative maintenance on FCS and FDS equipment; evaluating target data; identifying and engaging targets; performing operational and intelligence duties; operating / performing preventative maintenance on PATRIOT system prime movers and power units; and establishing and maintaining radio and wire communications." This MOS has a physical demands rating of "medium" and requires normal color vision.

MOS 14E was examined using a binary logistic regression model. Results are presented in Table 5. Because the logistic analysis data set was derived from actual school records for each student, individuals whose class was ongoing could not be included as part of the sample. For this reason, the logistic analysis was conducted using data for the 366 Soldiers who had completed the class.

Table 4.
14E: Correlations

	CL	CO	EL	FA	GM	MM	OF	SC	ST	GT	STUDAVG
CL	1.000										
CO	.652	1.000									
EL	.896	.619	1.000								
FA	.872	.813	.790	1.000							
GM	.641	.595	.856	.565	1.000						
MM	.412	.731	.568	.499	.739	1.000					
OF	.556	.820	.552	.607	.631	.853	1.000				
SC	.680	.876	.689	.705	.716	.755	.846	1.000			
ST	.853	.649	.887	.811	.789	.549	.666	.743	1.000		
GT	.909	.705	.816	.793	.598	.461	.618	.789	.779	1.000	
STUDAVG	.216	.177	.195	.233	.156	.104	.130	.152	.191	.181	1.000

All correlations significant at the $p < .001$ level.

From Table 5 we see that the model explains 9% of the variation in the dependent variable. Table 7 presents the predicted probability of passing for those who actually passed / failed the course. The standard errors between the two groups preclude much overlap between those who pass and those who fail, and the model predicts that the probability of passing for the group of subjects who failed is five percentage points lower than that for the group that passed. In this sense, although the absolute chance of passing is somewhat high for both groups, the model presented in Table 5 nevertheless seems to be capturing important features of the data.

Table 5.
14E: Results of the binary logistic prediction equation

Chi-Square		16.59*		
Log likelihood		235.97		
Nagelkerke R^2		.089		
		Coefficient	*Odds Ratio*	*Wald*
	Constant	-5.82	.003	3.57*
	Female	.91	2.48	1.44
	GED	-1.10	.33	6.73*
	College	.75	2.10	.51
	MM	.07	1.07	6.60*

* Significant at the .05 level
** Significant at the .001 level

Table 6.
14E: Chance that Soldiers from a given demographic group will pass the course.

	Male	Female
GED	74.5%	84.1%
HS	89.8%	94.6%
College	95.5%	97.4%

Table 7.
14E: Average predicted probability of passing among students who actually passed or failed the course

	Mean	Standard Error	Number
Pass	89.6%	.4%	326
Fail	85.0%	1.3%	40

The model suggests that having a higher MM composite score significantly predicts increased odds of passing. The marginal effect was relatively strong: at the mean MM score, an increase of 1 MM point is associated with an increase of 7% in the odds of passing the course, and a 5 point increase in MM would increase the odds of passing by 40%. Also, the impact of not having a high school diploma was quite striking (see Figure 1): the odds of passing the course for students with only a GED were 67% less.

Table 6 presents the probability that the average Soldier in the data sample with given demographic characteristics will pass MOS 14E. (Keep in mind that the male / female differences shown in the table are not statistically significant.) This further demonstrates the difference between students having a GED and those with more education. On average the probability that a male Soldier will pass the course increases by fifteen percentage points if he has earned a high school diploma. Female Soldiers see a smaller but also striking effect. This, combined with the marginal effects reported in Table 5, suggests that being a high school graduate may be the single biggest influence on whether a Soldier will pass the course.

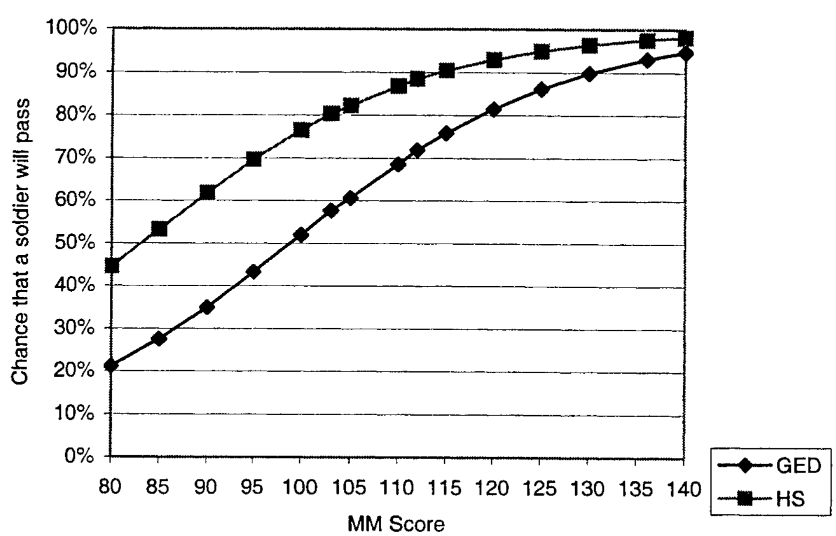
Table 8.
14E: Probability that an average Soldier will pass the course based on the binary logistic model[6].

	Cutoff MM = 105	Cutoff MM = 100	No Cutoff
Mean	115.22	112.27	103.29
Men GED	77.5%	73.7%	59.7%
Men HS	91.2%	89.3%	81.6%
Men College	95.6%	94.6%	90.3%

Policy Analysis:
Table 8 reports the probability that the average student (from the larger successful applicant population) would pass the course based on the binary logistic model.[7] These were calculated using the formula for finding probability in a binary logistic model, which is

$$e^{(\beta' x)} / (1 + e^{(\beta' x)}).$$

Figure 1: Chance that the average male 14E Soldier will pass with a given MM score



[6] The overall MM mean when cutoff is 105 = 115.22; when cutoff is 100 = 112.27; when there is no cutoff = 103.29.

[7] For the policy analysis, AA composite means were calculated from the Enlisted Accession File, U.S. Army Recruiting command, and refer to those meeting the particular eligibility standards for the population of those signing enlistment contracts during CY 1997-2000.

Because men comprise 90% of the students and because gender was not a statistically significant factor, the policy analysis is confined to males (but the findings would be similar for males and females combined). When the cutoff score is at its current level (MM = 105), students with an average MM score (MM = 115.22) with a high school diploma or more education have upwards of 90% probability of passing. Men with only a GED have a substantially lower probability of passing.

Figure 1 shows the relationship between MM and probability of passing. One can see the pronounced difference between students with a high school diploma and those without one. For those who score at the current cutoff (MM = 105) a student with a high school diploma is predicted to have over an 80% probability of passing, while one without a high school diploma has only about a 60% probability of passing. Also of note is the steep decline in the chance a student will pass as his MM score decreases.

Suppose that the school proponent considers lowering entrance criteria in order to facilitate meeting accession goals. If the governing composite cutoff score is lowered by 5 points (to MM = 100), the probability that a high school graduate with an average MM score would pass the course decreases slightly to just under 90%, and the probability that a non-high school graduate with an average MM score would pass falls somewhat more to just under 75% (Table 8).[8]

55B: Ammunition specialist[9]

Results. Descriptive statistics are reported in Table 9. The final sample of 207 Soldiers consisted of those who had passed the course or failed to complete the course for academic reasons, and had scored 95 points (or a "waiverable" 92) on the governing AA composite, Skilled Technical (ST). The mean Student Average was 92.8, with a standard deviation of 3.8.

Table 9.
55B: Means table for composites and Student Average

Variable	Mean	Standard Deviation	Minimum	Maximum
Student Average	**92.8**	**3.8**	**99.8**	**82.5**
CL	105.5	9.5	87	129
CO	103.5	12.1	76	135
EL	104.4	9.7	86	135
FA	105.8	11.0	80	133
GM	103.6	10.4	83	136
MM	103.6	77.8	74	135
OF	105.6	10.0	80	134
SC	104.1	11.1	84	134
ST	107.7	7.6	92	133
GT	105.2	9.7	86	125

8 The probability that a high school graduate with an MM score exactly at the cutoff would pass would decrease to just below 80%, and the probability of passing for a non-high school graduate with an MM score exactly at the cutoff would fall to about 50%.

9 The Military Occupational Classification and Organizational Structure pamphlet (611-211) describes the duties of a skill level one 55B graduate as "assists in the receipt, storage, issue, maintenance, modification, destruction, and demilitarization of explosive items; performs ammunition supply stock control and accounting duties using both automated and manual procedures; operates heavy equipment to maneuver ammunition." This MOS has a physical demands rating of "very heavy" and requires normal color vision, no allergies to explosive components, and no claustrophobic tendencies.

Table 10.
55B: Correlations

	CL	CO	EL	FA	GM	MM	OF	SC	ST	GT	STUDAVG
CL	1.000										
CO	.631	1.000									
EL	.833	.645	1.000								
FA	.802	.839	.686	1.000							
GM	.551	.671	.850	.500	1.000						
MM	.451	.825	.660	.597	.832	1.000					
OF	.531	.845	.592	.628	.712	.920	1.000				
SC	.661	.889	.724	.712	.774	.830	.846	1.000			
ST	.777	.642	.822	.667	.748	.629	.707	.745	1.000		
GT	.865	.644	.763	.671	.527	.485	.551	.742	.665	1.000	
STUDAVG	.388	.484	.393	.431	.412	.432	.445	.433	.359	.384	1.000

All correlations significant at the $p < .001$ level.

As shown in Table 10, AA composites are moderately to highly correlated. Student Average was most highly correlated with the Combat (CO) composite and least correlated with ST, the governing AA composite. Here too, restriction in range may be at work.

Given the absence of any academic failures in the data sample, we could not estimate pass/fail models, and so we estimated a continuous model using Student Average score as the dependent variable. Figure 2 is a histogram representing the participants in MOS 55B with their final outcome scores. Since only two students had perfect scores in the course, censoring is probably not a problem and thus OLS regression was used to analyze this data.

Figure 2
Histogram of Student Average outcome scores.

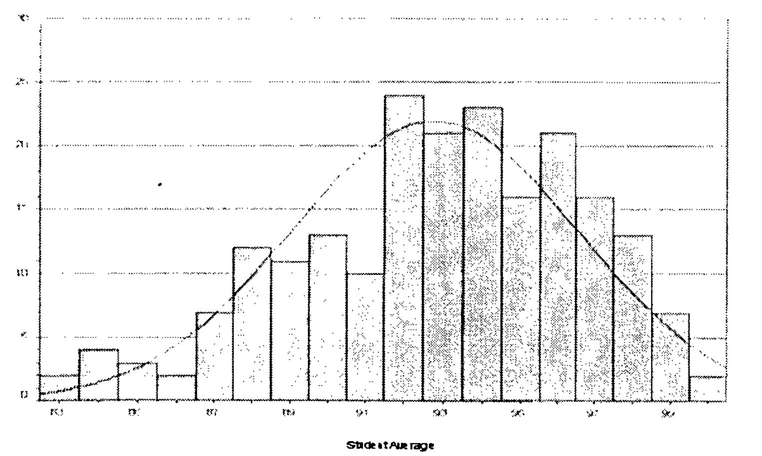


Table 11 presents the OLS results for the model that includes gender, education status, and the governing AA composite, ST. Significant effects were found for educational status, where (surprisingly) students with a GED performed better than those with a high school diploma; and for ST, where students with a higher ST score performed better. The ST effect is relatively weak: at the mean, a 10% increase in ST is associated with a 2.2% increase in Student Average score.

Policy Analysis. Predicted scores for the OLS model are presented in Table 12. (Male / female differences are small and not statistically significant.) Given the researchers' focus on changes in predicted Student Average when the cutoff score for the governing AA composite is varied, predictions were calculated at the current cutoff score, at the cutoff score reduced by five points, and with no cutoff score on the governing AA composite. For the prediction of the OLS model, we used the means of the governing AA composite in the successful applicant population at each cut off level[10], as well as the minimum score for the governing AA composite at its current level and when reduced by five points.[11] As can be seen in the table, for MOS 55B, altering the governing AA composite cutoff score is estimated to have little impact upon predicted score.

Table 11.
55B: Coefficients and significance for the OLS model

Variable	*Means*	*Coefficient*	*t-value*
	$F(4,140) = 7.03$** $r^2 = .143$		
Constant		71.51	17.08**
Female	.22	.54	.73
Has GED or less	.13	2.09	2.45*
Has some college	.02	.14	.07
ST	107.70	.19	4.88**

* Significant at the .05 level
** Significant at the .001 level

Table 12.
55B: Predicted baseline averages when ST cutoff is varied in the OLS Model.

		Predicted Student Average OLS Model					
Cutoff Scores	ST Average	Men GED	Women GED	Men High School	Women High School	Men College	Women College
ST = 95	110.1	94.5	95.1	92.4	93.0	92.6	93.1
ST = 90	108.1	94.1	94.7	92.0	92.6	92.2	92.7
No cutoff	106.5	93.8	94.4	91.7	92.3	91.9	92.4
Minimum, ST=95	95	91.7	92.2	89.6	90.1	89.7	90.24
Minimum, ST=90	90	90.7	91.24	88.6	89.2	88.8	89.3

[10] AA composite means were calculated from the Enlisted Accession File, U.S. Army Recruiting command, and refer to those meeting the particular eligibility standards for the population of those signing enlistment contracts during CY 1997-2000.

[11] For example, the mean predicted Student Average for a male Soldier who has earned a high school degree, assessed at the current governing AA composite and using the OLS estimation equation is

$$\hat{y}_{bar} = (\beta' x_{bar}) = 71.51 + (.54 * 0) + (2.09 * 0)*(.14 * 0) + (.19 * 110.1) = 92.4$$

where the constant is 71.51; (.54) is the coefficient for gender; (2.09) is the coefficient for GED; (.14) is the coefficient for College; and (.19) is the coefficient for MM.

Table 13 shows that the percentage of male students predicted to pass the course did not change when the governing AA composite cutoff score was lowed by 5 points. (Similar results hold for females.) To predict this, the standard error of the mean for predicted Student Average was calculated using the formula

$$\text{Standard Error} = \sqrt{[\Sigma(\text{residual}^2)]/(N-2)},$$

where $\Sigma(\text{residual}^2)$ is the sum of the squared differences between the predicted Student Average score for each participant and the actual score, and N is the number of participants. To determine the percentage of students who would pass the course at a given cut off score, a z-score was created by using the formula

$$(70 - \hat{y}_{bar}) / SE,$$

where 70 is the minimum score needed to pass the course, $\hat{y}_{bar}$ is the mean predicted score, and SE is the estimated standard error[12]. A z-table was used to determine what proportion of scores was greater than the calculated z-score. The analysis suggested that, at both cutoff levels, essentially all students are expected to pass the course.

Table 13.
55B: Percent of students predicted to pass the course.

		ST = 95	ST = 90
Men	GED	100%	100%
	High School	100%	100%
	College	100%	100%

55D: Explosive ordinance disposal (EOD) specialist[13]

Results. Descriptive statistics are reported in Table 14. The final sample of 92 Soldiers consisted of those who had passed the course or failed to complete the course for academic reasons, and had scored at least 105 points (or a "waiverable" 102) on the governing AA composite, General Maintenance (GM).

Table 14.
55D: Means table for composites and Student Average

Variable	Mean	Standard Deviation	Minimum	Maximum
Student Average	**87.9**	**9.6**	**20.1**	**98**
CL	117.7	9.1	99	134
CO	119.7	8.6	100	140
EL	119.0	9.0	104	140
FA	112.5	9.6	100	142
GM	119.1	8.3	105	142
MM	119.0	9.1	102	143
OF	118.8	8.5	101	137
SC	119.6	8.1	104	137
ST	121.5	8.8	104	139
GT	116.1	8.5	91	130

[12] This estimate was unbiased when applied to the population mean at the current governing AA composite. The estimated standard error is biased when applied to the populations with the cut off for the governing AA composite five points lower and with no AA governing composite cut off, because the current sample is not drawn from these populations.

[13] The Military Occupational Classification and Organizational Structure pamphlet (611-211) describes the duties of a skill level one 55D graduate as "researches and identifies ordnance using EOD technical publications; detects the presence of and identifies chemical agents; prepares and maintains EOD tools, equipment, and vehicles; assists in operating an Emergency Contamination Control Station and Emergency Personnel Decontamination Station; assists in locating and gaining access to buried ordnance; and assists the EOD Team Leader in performing major duties." This MOS has a physical demands rating of "very heavy" and requires normal color vision, no allergies to explosives, and the ability to wear protective clothing. This MOS is open to volunteers only.

The mean Student Average was 87.9, with a standard deviation of 9.6.

As demonstrated in Table 15, composites are moderately to highly correlated. Student Average was most highly correlated with the ST composite, least correlated with General Technical (GT), and somewhat correlated with the governing composite.

Table 15.
55D: Correlations

	CL	CO	EL	FA	GM	MM	OF	SC	ST	GT	STUDAVG
CL	1.000										
CO	.613	1.000									
EL	.908	.659	1.000								
FA	.865	.823	.809	1.000							
GM	.667	.746	.855	.659	1.000						
MM	.505	.801	.652	.602	.820	1.000					
OF	.588	.830	.622	.671	.762	.912	1.000				
SC	.662	.844	.711	.658	.778	.815	.864	1.000			
ST	.800	.636	.827	.778	.761	.567	.716	.761	1.000		
GT	.892	.584	.833	.692	.574	.480	.561	.725	.691	1.000	
STUDAVG	.280*	.119ˣ	.266*	.292*	.257*	.148ˣ	.180ˣ	.145ˣ	.359*	.105ˣ	1.000

All correlations significant at the .001 level unless otherwise noted.
* Correlation significant at the .05 level.
ˣ Correlation is not significant at the .05 level.

The model examined for MOS 55D was the binary logistic regression model. The results are presented in Table 16. Because the logistic analysis was derived from school records for each student, individuals whose class was ongoing could not be included as part of the sample. For this reason, the logistic analysis was completed using data from only 37 Soldiers who had completed the class. In addition, none of these participants had less than a high school diploma, and only one had some college education. Thus, no education status variables were used in estimating the binary logistic model.

The estimated model suggested that having a higher GM composite score significantly predicted increased odds of passing. The effect was very strong: at the mean, a one-point increase in the GM composite is associated with an increase in the odds of passing of 21%, and an increase of five points increases the odds of passing by over 150%. The estimated gender effect was not significant (there were only five females in the sample), and so the policy analysis refers only to male Soldiers.

Table 16.
55D: Results of the binary logistic prediction equation

Chi-Square	11.36*		
-2 Log likelihood	36.61		
Nagelkerke R^2	.358		
	coefficient	*Odds Ratio*	*Wald*
Constant	-21.92	.00	6.84*
Female	.68	1.97	.32
GM	.19	1.21	7.8*

* Significant at the .05 level
** Significant at the .001 level

With regard to goodness of fit, from Table 16 we see that the model accounts for 35% of the variation in the dependent variable, using the Nagelkerke approximation to the R^2. In Table 18 we see the predicted probability of passing by those who actually passed / failed the course. On average, students who actually passed the course had a 25 percentage-point higher predicted probability of passing than those who actually failed the course. This, coupled with relatively small standard errors, suggests that the model provides a reasonably good fit to the data.

Table 18.
55D: Average predicted probability of passing among students who actually passed or failed the course.

	Mean	Standard Error	Number	Average GM Score
Pass	73.7%	5.1%	33	120.88
Fail	48.5%	4.9%	14	112.46

Policy Analysis. Table 19 reports the probability that the average male student (from the successful applicant population) would pass the course based on the binary logistic model[14]. These were calculated using the formula for finding probability in a binary logistic model, which is

$$e^{(\beta' x)} / (1 + e^{(\beta' x)}).$$

When the cutoff score is at its current level (GM = 105), the average male Soldier (with a GM score = 114.77) will have better than a 55% probability of passing. From this point the probability of passing drops precipitously as the GM scores decreases, as shown in Figure 3.

Table 19.
55D: Percent chance that an average Soldier will pass the course based on the binary logistic model[15].

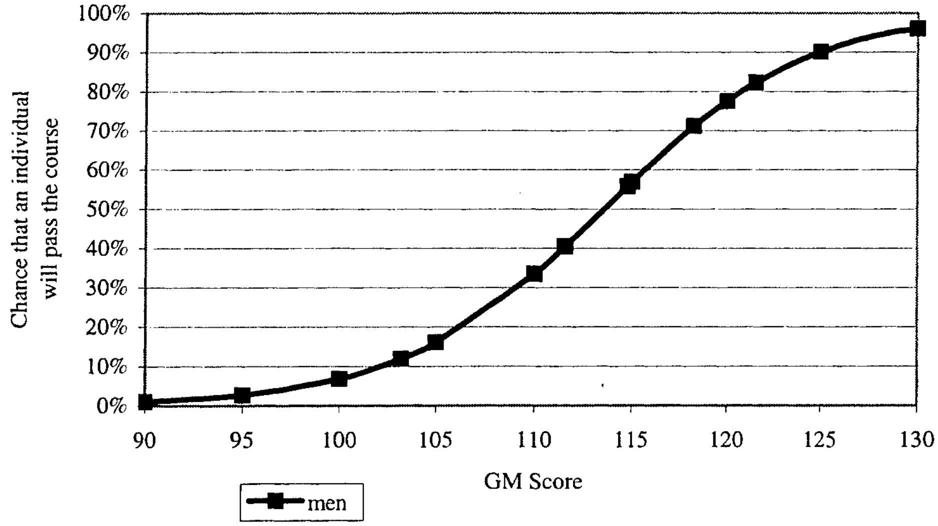
	Cutoff GM = 115	Cutoff GM = 110	Cutoff GM = 105	Cutoff GM = 100	Mean with No Cutoff
Men	82%	71%	56%	40%	12%

Suppose that the school proponent considers raising entrance criteria in order to reduce attrition. In fact, if the MOS 55D proponent were to raise the cutoff score by 10 points (i.e., to GM=115), the average (male) student would have more than an 80% probability of passing, up from 56%, and the student just barely qualifying for the course would still have better than a 55% probability of passing. The school would be more efficient, but this could lower enrollment enough to prevent the MOS from meeting its enlistment quota. Though this is a legitimate concern, it is mitigated by the fact that for those who actually failed the course, the mean GM score was 112.5. In other words, some / many of the people who would not qualify for the school under the higher standard would probably not pass the course anyway.

[14] AA composite means were calculated from the Enlisted Accession File, U.S. Army Recruiting command, and refer to those meeting the particular eligibility standards for the population of those signing enlistment contracts during CY 1997-2000

[15] Overall GM mean when cut off is 105 = 114.77; when cut off is 100 = 111.55; when there is no cutoff = 103.20.

Figure 3: Chance that the average male 55D Soldier will pass with a given GM score



77F: Petroleum specialist[16]

Results. Descriptive statistics are reported in Table 20. The final sample of 3285 Soldiers consisted of those who had passed the course or failed to complete the course for academic reasons, and had scored at least 90 points (or a "waiverable" 87) on each of the governing AA composites, Clerical (CL) and Operators / Food (OF). The mean for Student Average was 88.4, with a standard deviation of 7.1.

Table 20.
77F: Means table for composites and Student Average

Variable	Mean	Standard Deviation	Minimum	Maximum
Student Average	**88.4**	**7.1**	**3.2**	**100**
CL	101.0	9.5	87	134
CO	98.2	11.5	67	140
EL	97.4	11.0	70	140
FA	101.3	10.9	73	143
GM	95.3	11.5	67	140
MM	96.9	10.8	71	140
OF	99.7	9.1	87	134
SC	96.7	11.3	74	135
ST	98.9	10.5	74	139
GT	100.0	9.7	75	133

As shown in Table 21, composites are moderately to highly correlated for students in 77F MOS. Student Average was most highly correlated with the Field Artillery (FA) composite, least correlated with MM, and somewhat correlated with the governing composites. Once again, we suspect that range restriction on the governing composites is at work.

[16] The Military Occupational Classification and Organizational Structure pamphlet (611-211) describes the duties of a skill level one 77F graduate as "receives and stores bulk and package POL products; issues and dispenses bulk fuels and water from storage and distribution facilities to units; selects and submits samples of POL to laboratory for testing; performs petroleum and water accounting duties; operates equipment associated with petroleum and water distribution system and multi-product pipeline system; fuels and de-fuels vehicles, aircraft, and stationary equipment; takes emergency precautions to prevent harm to self and facilities in event of petroleum spillage or fire." This MOS has a physical demands rating of "very heavy" and requires normal color vision and a valid state driver's license.

Table 21.
77F: Correlations

	CL	CO	EL	FA	GM	MM	OF	SC	ST	GT	STUDAVG
CL	1.00										
CO	.662	1.00									
EL	.864	.717	1.00								
FA	.823	.851	.763	1.00							
GM	.674	.718	.906	.613	1.00						
MM	.521	.822	.735	.636	.842	1.00					
OF	.616	.846	.696	.670	.773	.919	1.00				
SC	.693	.891	.773	.703	.817	.853	.892	1.00			
ST	.802	.708	.880	.742	.854	.705	.780	.807	1.00		
GT	.886	.708	.792	.709	.635	.559	.668	.796	7.36	1.00	
STUDAVG	.303	.305	.300	.313	.279	.270	.285	.288	.280	.283	1.00

All correlations significant at the $p < .001$ level.

The MOS 77F data sample contained almost no academic failures (i.e., 13 out of 2678 Soldier records). Accordingly, we estimated the continuous model using Student Average score as the dependent variable. Figure 4 is a histogram representing the participants in MOS 77F who had final outcome scores. This showed that almost 50 participants had a perfect score for the course. Therefore, censoring at the top of the distribution is a possibility and both OLS and censored regression models were estimated.

Figure 4
Histogram of Student Average outcome scores.

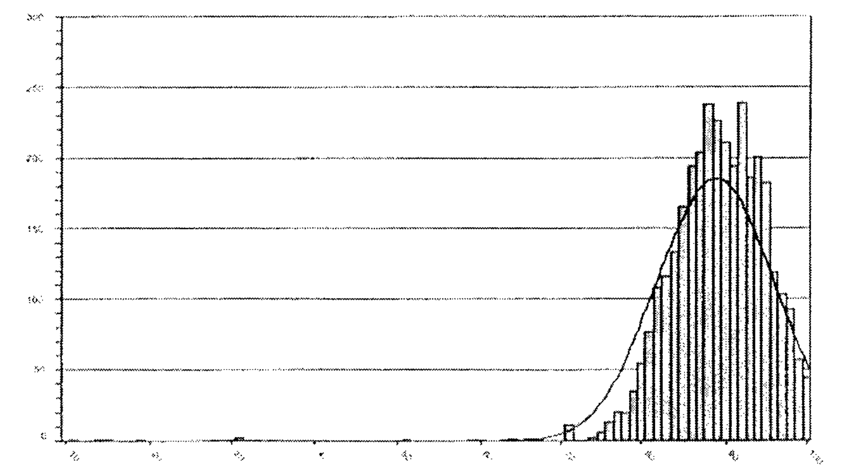


Table 22 presents the OLS results for a model that includes gender, education status, and the governing AA composites. Significant effects were noted for gender, where male students performed better than female students; for CL, where students with a higher CL score preformed better; and for OF where students with a higher OF performed better. Evaluated at the composite means, a 10% increase in the CL (OF) composite is associated with less than a 2% increase in Student Average score.

Coefficients and significance for the censored model are also included in Table 22. In this model gender, CL, and OF remained significant predictors of Student Average. In addition, the bias term (sigma) was highly significant. However, the bias term has little impact upon the application of the model. This is demonstrated in the fact that two times sigma, which is the standard deviation of the bias, is barely more than the censored point (i.e., 100). This means that less than 2.5% of the cases have the possibility of being censored, which is too small to make censoring an issue.

Coefficients and significance for the censored model are also included in Table 22. In this model gender, CL, and OF remained significant predictors of Student Average. In addition, the bias term (sigma) was highly significant. However, the bias term has little impact upon the application of the model. This is demonstrated in the fact that two times sigma, which is the standard deviation of the bias, is barely more than the censored point (i.e., 100). This means that less than 2.5% of the cases have the possibility of being censored, which is too small to make censoring an issue.

Table 22.
77F: Coefficients and significance for the OLS and censored models

	Variable	Means	Coefficient	t-value
OLS	F(5,3237) = 79.28 $r^2 = .11$			
	Constant		59.91	41.21**
	Female	.28	-.67	-2.46*
	Has GED or less	.09	.14	.34
	Has some college	.06	.24	.47
	CL	101.04	.15	9.48**
	OF	99.65	.13	7.82**
Censored Model	Log likelihood = -10754.36			
	Constant		59.91	48.46**
	Female	.28	-.67	-2.50*
	Has GED or less	.09	.14	.31
	Has some college	.06	.23	.49
	CL	101.04	.15	9.52**
	OF	99.65	.13	7.83**
	Sigma		6.67	80.23**

* Significant at the .05 level
** Significant at the .001 level

Policy Analysis. Predicted student scores for the OLS model are presented in Table 23. Given the researchers' focus on changes in predicted Student Average when the cutoff scores for the governing AA composite are varied, predictions were calculated at the current cutoff scores, at the cutoff scores reduced by five points, and with no cutoff score on the governing AA composites. For the prediction of both OLS and censored models (not shown), we used the means of the AA composite scores in the successful applicant population at teach cut off level[17], as well as the minimum score for the governing AA composites at their current levels and when

[17] AA composite means were calculated from the Enlisted Accession File, U.S. Army Recruiting command, and refer to those meeting the particular eligibility standards for the population of those signing enlistment contracts during CY 1997-2000.

reduced by five points.[18] As can be seen in the table for MOS 77F, altering the governing AA composite cutoff scores are estimated to have little impact upon predicted Student Average score.

Table 23.
77F: Predicted baseline averages when CL and OF cutoff is varied in the OLS model.

			Predicted Student Average OLS model					
Cutoff Scores	CL Average	OF Average	Men GED	Women GED	Men High School	Women High School	Men College	Women College
CL = 90, OF = 90	108.2	107.3	91.8	91.1	91.6	91.0	91.9	91.2
CL = 85, OF =85	106.9	105.9	91.4	90.7	91.2	90.6	91.5	90.8
No cutoff	106.5	105.1	91.2	90.5	91.1	90.4	91.3	90.6
Minimum, CL = 90, OF = 90	90	90	86.7	86.1	86.6	85.9	86.8	86.2
Minimum, CL = 85, OF = 85	85	85	85.3	84.6	85.2	84.5	85.4	84.7

Table 24 shows that the percent of students predicted to pass the course at the current governing AA composite cutoff scores and when the cutoff scores were lowered by 5 points. To predict this, the standard error of the mean for predicted Student Average was calculated using the formula

$$\text{Standard Error} = \sqrt{[\Sigma(\text{residual}^2)]/(N-2)}\ ,$$

where $\Sigma(\text{residual}^2)$ is the sum of the squared differences between the predicted Student Average score for each participant and the actual score, and N is the number of participants. To determine the percentage of students who would pass the course at a given cut off score, a z-score was created by using the formula

$$(70 - \hat{y}_{bar}) \ / \ SE,$$

where 70 is the minimum score needed to pass the course, $\hat{y}_{bar\,r}$ is the mean predicted score, and SE is the estimated standard

Table 24.
77F: Percent of students predicted to pass the course.

		CL = 85 OF = 85	CL = 90 OF = 90
Male	GED	99.95%	99.93%
	High School	99.94%	99.93%
	College	100%	99.94%
Female	GED	99.92%	99.91%
	High School	99.92%	99.90%
	College	99.93%	99.91%

[18] For example, the mean predicted Student Average for a male Soldier who has earned a high school degree, assessed at the current governing AA composite and using the OLS estimation equation is

$$\hat{y}_{bar} = (\beta' x_{bar}) = 61.25 + (-.67 * 0) + (.14 * 0)*(.24 * 0) + (.15 * 108.28) + (.13 * 107.39) = 87.15$$

where the constant is 61.25; (-.67) is the coefficient for gender; (.14) is the coefficient for GED; (24) is the coefficient for College; (.15) is the coefficient for CL, and (.13) is the coefficient for OF.

error.[19] A z-table was used to determine what proportion of the scores was greater than the calculated z-score.

Summary and Conclusion

The purpose of this study was to begin exploration of the impact of minimum enlistment standards (i.e., cut-scores) upon training attrition / completion and student training performance. We found individual Soldier training performance data available in AIMS / ATSC for some MOS, and obtained data sets for MOS 14E (Patriot fire control operator/maintainer), 55B (ammunition specialist), 55D (explosive ordnance disposal specialist), and 77F (petroleum specialist) for AIT classes held over the 1999 – 2000 period. During the period under study, the unit-weighted AA composites were in effect; these were replaced in January 2002 with least-squares weighted composites, and so the empirical results reported here will be re-examined when sufficient data under the new composite regime are available.

We specified and estimated binary logistic models based on course-level pass / fail data and regression models using overall Student Average data. These criteria, or dependent variables, were estimated as functions of AA governing composites and Soldier demographic variables. We found moderate correlations between student performance and AA composites (and note that restriction-in-range effects were not taken into account), and relatively modest explanatory power of the estimated logistic and OLS regression models. The (statistically significant) results can be summarized as follows:

a. For 14E training attrition, estimated with the binary logistic model – we found that the MM composite effect was strong, and that the GED effect was negative. Reducing the cut-off score by 5 points was estimated to reduce the probability of passing by 2 percentage points for high school graduates, and by more for GED.

b. For 55D training attrition, estimated with the binary logistic model – we found that the GM composite effect was strong; however, the data set was relatively small (47 observations). There may be an efficiency argument for raising the cut-score to reduce attrition.

c. For 55B training performance, there were no academic failures in the data set, and we estimated an OLS regression model. We found a weak ST composite effect, and a GED effect that was positive! Altering governing composite cut-score had little impact upon predicted Student Average score.

d. For 77F training performance, there were essentially no academic failures in the data set, and we estimated OLS and censored regression models. We found weak CL

[19] This estimate was unbiased when applied to the population mean at the current governing AA composite. The estimated standard error is biased when applied to the populations with the cut off for the governing AA composite five points lower and with no AA governing composite cut off, because the current sample is not drawn from these populations.

and OF effects. Altering governing composites' cut-scores had little impact upon predicted Student Average score.

While the MOS for which detailed training performance data were obtained cannot be considered representative, they illustrated the difficulties of the intended exploration. AIT is closely managed; with the data available it is not always possible to distinguish the better from the poorer students. In particular, it is difficult to accurately distinguish between failure to complete training due to academic versus non-academic reasons; there is not much variation in student training performance scores; and there would appear to be a lot of ongoing student remediation.

The estimation and analyses we undertook were at a course level. We found the pass/fail logistic model to be most directly applicable to the kind of policy analysis we envision (in contrast to the "indirect" estimation of the determinants of training performance scores). However, the training management environment and kinds of data limitations described above may push future research toward use of a more complicated modeling framework in which individual instruction block outcomes (and not just the final course outcome) are considered.

In conclusion, we have taken the initial step in establishing the feasibility of doing this kind of policy analysis but are not there yet. The research is likely to prove worthwhile if we can find MOS where there is sufficient variation in student performance and training outcomes, and/or if we are able to specify and test more complicated models that utilize more of the inherent variation in the instruction blocks.

In closing, we note that the objective at hand involves the use of training performance data and the development of defensible MOS cutoff level scores, and is not a surrogate for additional validation of the ASVAB. The ASVAB, which forms the basis of the Army's AA composites, has been validated and proven to be a good predictor of Soldier job performance – albeit with Soldier performance data that is 15 years old (Oppler et al., 2001). There is ongoing research (PerformM21) into the feasibility of re-instituting a Soldier performance assessment program within the Selection and Assignment Research Unit at the Army Research Institute. The aim of such a future program would be to provide the Army with the current data needed to assess the training and performance of Soldiers, as well as to provide ARI with performance criterion data needed in the development of new selection and classification predictors.

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Appendix A:
AA Composite Structures

To select and classify recruits to job training, the Army employs nine Aptitude Area (AA) composites. Each composite represents a differentially weighted function of aptitudes and skills required for successful performance. Until recently, these nine AA composites utilized unit-weights (i.e., 0, 1). Based on rational linkages to job content, these unit weights were meant to reflect the relative importance of different cognitive aptitudes and abilities (e.g., verbal ability, coding speed, mechanical comprehension), as measured by the Armed Services Vocational Battery (ASVAB), in determining job performance within a family of jobs (e.g., Clerical, Combat, Field Artillery, etc.). These "original", unit-weighted AA composites and corresponding ASVAB subtests are shown in Table 1.

Table 1: ASVAB Subtests Comprising the Army's "Original" AA Composites and AFQT

	ASVAB SUBTESTS								
	AR	MK	VE	AS	EI	GS	MC	CS	NO
AA COMPOSITES									
Electronics Repair	X	X			X	X			
General Maintenance		X		X	X	X			
Mechanical Maintenance				X	X		X		X
Operators / Food			X	X			X		X
Surveillance / Communications	X		X	X			X		
Combat	X			X			X	X	
Field Artillery	X	X					X	X	
Skilled Technical		X	X			X	X		
Clerical	X	X	X						
General Technical	X		X						
AFQT	X	X	XX						

ASVAB is comprised of following subtests: Arithmetic Reasoning (AR), Math Knowledge (MK), Verbal (VE) = Paragraph Comprehension (PC) + Word Knowledge (WK), Auto & Shop Information (AS), Electronics Information (EI), General Science (GS), Mechanical Comprehension (MC), Coding Speed (CS), Numerical Operations (NO).

Starting in January 2002, the Army adopted a set of nine AA composites based on empirically estimated beta weights, corrected to the Youth population, for a 7 ASVAB test battery (Greenston, Rumsey, Zeidner, & Johnson, 2001). The ASVAB subtest weights that define the AA composites are shown in Table 2. These composites were developed by Zeidner, Johnson, and colleagues (Zeidner, Johnson, Vladimirsky, & Weldon, 2001), with support from the Army Research Institute, as part of a proposed two-tiered classification system. In descriptions of the Zeidner, Johnson, and colleagues' method, these weights are frequently referred to as least squares estimates (LSE) or LSE weights, as the weights are empirically estimated using conventional ordinary least-squares (OLS) regression.

Table 2: ASVAB Subtest (Relative) Weights Comprising the AA Composites

	ASVAB Subtests						
	AR	MK	VE	AS	EI	GS	MC
AA COMPOSITES							
Electronics Repair	.818	.890	1.000	.754	.598	.151	.469
General Maintenance	.828	.794	.417	1.000	.577	.411	.503
Mechanical Maintenance	.339	.289	.237	1.000	.340	.060	.394
Operators / Food	.962	.600	.714	1.000	.377	.251	.636
Surveillance / Communications	.685	1.000	.915	.437	.551	.019	.386
Combat	.532	1.000	.529	.733	.343	.313	.595
Field Artillery	.715	1.000	.586	.673	.297	.249	.700
Skilled Technical	.727	.697	1.000	.357	.230	.187	.446
Clerical	1.000	.767	.980	.110	.110	.000	.148

Appendix B:

Reason Codes

Code	Reason
!P	NORMAL STUDENT INPROCESSING
#N	IN AIT/OSUT - ENTNAC RESULTS NOT RCVD
#O	IN AIT/OSUT - ENTNAC RESULTS NOT RCVD
#P	IN AIT/OSUT - ENTNAC RESULTS NOT RCVD
$O	TRAINING PREVIOUSLY COMPLETED
$P	TRAINING PREVIOUSLY COMPLETED
%N	DOES NOT MEET COURSE PREREQUISITES
%O	DOES NOT MEET COURSE PREREQUISITES
%P	DOES NOT MEET COURSE PREREQUISITES
&N	NONE
+N	AIT/OSUT COMPLETE - ENTAC RESULTS NOT RCVD
+O	AIT/OSUT COMPLETE - ENTAC RESULTS NOT RCVD
+P	AIT/OSUT COMPLETE - ENTAC RESULTS NOT RCVD
-N	SHOWED BUT RETURNED (LOW/OVER FILL)
-O	SHOWED BUT RETURNED (LOW/OVER FILL)
-P	SHOWED BUT RETURNED (LOW/OVER FILL)
1O	DRUG ABUSE
1P	DRUG ABUSE
2O	RETRAINING
2P	RETRAINING
3O	AWAITING ASSIGNMENT INSTRUCTIONS
3P	AWAITING ASSIGNMENT INSTRUCTIONS
4O	FOLLOW ON SCHOOL START
4P	FOLLOW ON SCHOOL START
5O	UCMJ - CM WITNESS
5P	UCMJ - CM WITNESS
6O	AWAITING SCHOOL START
6P	AWAITING SCHOOL START
7O	RECLASSIFICATION
7P	RECLASSIFICATION
8O	REMEDIAL TRAINING - ACADEMIC
8P	REMEDIAL TRAINING - ACADEMIC
9O	UCMJ - RESPONDENT
9P	UCMJ - RESPONDENT
<O	PENDING APPEAL
<P	PENDING APPEAL
=N	SECURITY CLRNCE OTHER THAN ENTNAC NOT RCVD
=O	SECURITY CLRNCE OTHER THAN ENTNAC NOT RCVD
=P	SECURITY CLRNCE OTHER THAN ENTNAC NOT RCVD
>O	2ND TIME NON-SUCCESSFUL COMPLETION
>P	2ND TIME NON-SUCCESSFUL COMPLETION
?N	DOSSIER RECIEVED, AWAITING REVIEW
?O	DOSSIER RECIEVED, AWAITING REVIEW
?P	DOSSIER RECIEVED, AWAITING REVIEW
@P	VALID RESERVATION
AD	CONVENIENCE OF THE GOVERNMENT
AO	COMPREHENSION/ACADEMIC
AP	COMPREHENSION/ACADEMIC
BD	EPTS - EXISTED PRIOR TO SERVICE
BO	PHYSICAL FITNESS (remedial tng - APFT)
BP	PHYSICAL FITNESS (remedial tng - APFT
CD	DEPENDENCY OR HARDSHIP
CO	MOTIVATIONAL
CP	MOTIVATIONAL
DD	DEFECTIVE ENLISTMENT AND INDUCTIONS
DO	LEADERSHIP SKILLS
DP	LEADERSHIP SKILLS
ED	ELS - GOOD OF THE SERVICE APFT FAILURE
EO	ENGLISH LANGUAGE COMPETENCY

EP	ENGLISH LANGUAGE COMPETENCY
FD	ELS - GOOD OF THE SERVICE BRM FAILURE
FO	MEDICAL SEPARATIONS
FP	MEDICAL SEPARATIONS
GD	ELS - GOOD OF THE SERVICE EOCT FAILURE
GO	DOES NOT MEET WEIGHT CONTROL STD. OF AR600-9
GP	DOES NOT MEET WEIGHT CONTROL STD. OF AR600-9
HD	ELS - GOOD OF THE SERVICE ACADEMIC FAILURE
HO	ACCELERATED IN TRAINING
HP	ACCELERATED IN TRAINING
ID	ELS - OTHER
IO	LEAVE EMERGENCY
IP	LEAVE EMERGENCY
JD	RECALL
JO	MEDICAL
JP	MEDICAL
KD	OTHER MEDICAL DISCHARGES
KO	DISCIPLINARY/MISCONDUCT
KP	DISCIPLINARY/MISCONDUCT
LD	OTHER
LO	COMPASSIONATE/DEPENDENCY /HARDSHIP
LP	COMPASSIONATE/DEPENDENCY /HARDSHIP
MD	ELS - FAILURE TO ADAPT
MO	AIRBORNE HOLD
MP	AIRBORNE HOLD
ND	ELS - LACK OF MOTIVATION
NO	UNIT RECALL
NP	UNIT RECALL
OD	PREGNANCY (AFTER ENTRY/MUST BE DISCH)
OO	ERRONEOUS ENROLLMENT
OP	ERRONEOUS ENROLLMENT
PD	REHAB FAILURE (ALCOHOL/OTH DRUG ABUSE)
PO	HOSPITALIZATION
PP	HOSPITALIZATION
QD	IN LIEU OF TRIAL BY COURT MARTIAL
QO	CONFINEMENT
QP	CONFINEMENT
RD	UNSATISFACTORY PERFORM (NON - ELS)
RO	AWOL, RETURN FROM
RP	AWOL, RETURN FROM
SD	MISCONDUCT
SO	SECURITY/FLAGGED UP AR600-31
SP	SECURITY/FLAGGED UP AR600-31
TD	HOMOSEXUAL CONDUCT
TO	TRAINEE DISCHARGE PROGRAM
TP	TRAINEE DISCHARGE PROGRAM
UD	DROP FROM ROLLS
UO	PORT CALL PENDING
UP	PORT CALL PENDING
VO	PERSONNEL ACTION PEND NOT OTHERWISE DEFINED
VP	PERSONNEL ACTION PEND NOT OTHERWISE DEFINED
WO	AWOL (FROM DUTY TO)
WP	AWOL (FROM DUTY TO)
XO	DESERTION
XP	DESERTION
YO	DA APPROVED HOLDOVER I.E. SPT BASE OP MISSION
YP	DA APPROVED HOLDOVER I.E. SPT BASE OP MISSION
ZO	OTHER, NOT IN OTHER REASON CATEGORY
ZP	OTHER, NOT IN OTHER REASON CATEGORY