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# **Predicting Performance in Army Aviation Primary Flight Training**

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U.S. Army Research Institute



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The Army Research Institute Aviation Research and Development Activity (ARIARDA) successfully implemented the Multi-Track Test Battery and associated classification functions in 1988. The battery and functions have been used to assign more than 4,000 flight students to their combat skills aircraft. The subsequent program determined the applicability of the battery to prediction of student performance in flight training. This report examines prediction of performance in the first 100 days of training. Performance evaluation in primary training consists of four flight-phase grades and 12 academic-phase grades. In addition to these, primary overall average grade and primary overall flight grade were predicted using forward stepwise multiple-regression procedures. Stepwise multiple-discriminant analysis was used to investigate two additional measures—flight deficiency training setback and flight deficiency attrition. The capability of the battery to predict primary training grades is demonstrated. Results of discriminant analysis of setbacks and attrition should be viewed with caution.					
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#### PREDICTING PERFORMANCE IN ARMY AVIATION PRIMARY FLIGHT TRAINING

CONTE	NTS		
		F	Page
INTRO	DUCT:	ION	1
метно	D .		2
		tion of Primary Grade Performance tion of Primary Setback and Attrition	2 4
RESUL!	rs .		4
Se	tbacl	tion of Primary Grades	4 6 9
DISCU	SSIO	N AND CONCLUSION	12
REFER	ENCE	s	13
APPENI	DIX:	REGRESSION ANALYSIS SUMMARY OF TEST BATTERY PREDICTING PRIMARY GRADES	A-1
		LIST OF TABLES	
Table	1.	Primary grades used in analyses	2
	2.	Multi-track test battery nomenclature	3
	3.	Summary results of multiple regressions on primary grades using test battery scores	5
	4.	Classification capability of test battery for setback versus non-setback students in primary training	7
	5.	Standardized canonical discriminant function coefficients for primary training setbacks	8
	6.	Classification function coefficients for primary training setbacks	8
	7.	Classification capability of test battery for attrite versus non-attrite students in primary training	10

#### CONTENTS (Continued)

			Page
Table	8.	Standardized canonical discriminant function coefficients for primary training attritions	11
	9.	Classification function coefficients for primary training attritions	11

### PREDICTING PERFORMANCE IN ARMY AVIATION PRIMARY FLIGHT TRAINING

#### Introduction

In May 1988, the U.S. Army Aviation Center (USAAVNC) initiated a new course of training for aviator candidates. new course, Initial Entry Rotary Wing-Multi-Track (IERW-MT), replaced the TH-55 helicopter with the UH-1 helicopter as the primary trainer. On Training Day (TD) 95, the candidates were assigned to one of four primary tracks or helicopters--UH-1, AH-1, OH-58, and UH-60--to complete advanced training and earn their The Army Research Institute Aviation Research and Development Activity (ARIARDA) developed a method of assigning candidates to one of these four tracks. ARIARDA developed a test battery and specific procedures for classifying aviator candidates into one of the four helicopters prior to TD 95. Discriminating measures were required to assign candidates to a helicopter in which they would have the highest probability of both successfully completing flight training and having a successful aviation career. A complete description of the research conducted for selecting a test battery is contained in Intano, Howse, and Lofaro, 1991a. The test battery and its derived classification functions and procedures were implemented by the USAAVNC in May of 1988. This entire classification process is operational and has been used to assign over 4000 aviator candidates to their helicopters for training. Track Test Battery and Classification Functions have been very successful in matching students with their optimum helicopters. The readers are referred to the validation of the multi-track battery reported in Intano, Howse, and Lofaro, 1991b; and Intano and Howse (in preparation), for a thorough description of the initial and final validation results.

As part of the initial validation, an attempt was made to determine if the test battery could predict actual student performance both in primary and advanced training. The initial results using 686 graduates provided strong indications that the test battery could predict performance in both training areas. Upon completion of the final validation research (Intano and Howse, in preparation), the researchers decided to determine if other performance measures, including academic and flight grades and attrition and training setbacks, could be predicted. The research included over 3000 graduates from 40 graduating classes in 1989 and 1990. This performance predictive capability would provide Army Aviation with an estimate of how well a potential candidate would perform in training.

#### Method

#### Prediction of Primary Grade Performance

Common Core or Primary Flight Training is conducted in the UH-1 helicopter. All students receive the same academic and flight training for the first 100 days of flight school. academic grade represents a block of classroom instruction, e.g., Aerodynamics. Each flight grade is the final check-flight grade for a particular phase of flying, e.g., Basic Instruments. composite grades are also to be considered; Primary Overall Average Grade (POAG) and Primary Overall Flight Grade (POFG). The POAG is an unweighted average of all percentage scores on primary evaluations. POFG is an unweighted average of all flight grade percentages in primary flight training. Table 1 presents the grade nomenclature used in the analyses. Forward Stepwise Multiple Regression Analyses were used to predict these grades. For all stepwise multiple regression analyses, the critical value for the probability of F-to-enter was set at 0.05, and tolerance was set at 0.01. Multi-Track Test Battery scores were used as candidate predictor variables. The candidate predictor variables and their nomenclatures are presented in Table 2.

Table 1
Primary Grades Used in Analyses

Administration		
Training	Grade	Grade
Day	Acronym	Title
5	EA01	Aviation Medicine
9	EA02	Flight Support
14	EA03	Aerodynamics
19	EA06	UH-1 Systems (Part 1)
23	EA07	UH-1 Systems (Part 2)
34	EF01	Primary Flight - Stage 1 (Contact)
36	EA04	Weather
46	EA05	Navigation
58	EA12	Survival, Escape, Resistance, Evasion
60	EF02	Primary Flight - Stage 2 (Solo)
66	EA08	Instruments - Part 1
73	EA09	Instruments - Part 2
79	EA10	Instruments - Part 3
80	EF03	<pre>UH-1 Simulator Instrument Flight</pre>
82	EA23	Instrument Flight Evaluation and Critique
86	EA17	Terrain Flight Operations
100	EF04	UH-1 Instrument Flight

Table 2
Multi-Track Test Battery Nomenclature

Acronyms	Name
	Complex Cognitive Assessment Battery (CCAB), (Samet et al, 1986)
WORDANA TOWER MARKNUM NUMWORDS INFOPUR	Word Anagrams Tower Puzzle Mark Numbers Numbers and Words Information Purchase
<u>Basi</u>	c Attributes Tests (BAT), (Siem and Carretta, 1986)
WORDKNOW MANIKIN	Word Knowledge Manikin Test
c 	cockpit Management Attitude Questionnaire (CMAQ), (Helmreich, 1987)
COMP25 COMP15 COCKPIT LEADER VULNER CLUSTER1 CLUSTER2 CLUSTER3 CLUSTER4 CLUSTER5	Performance Related Composite (25 Questions) Performance Related Composite (15 Questions) Cockpit Procedure and Atmosphere Leadership Vulnerability Item Cluster 1 Item Cluster 2 Item Cluster 3 Item Cluster 4 Item Cluster 5
Co	omplex Coordination/Multi-Tasking Battery (CCMB), (Griffin and McBride, 1986)
SDLT DDLT1 DDLT2 DDLT3 SPSY6 SDSY1	Single Dichotic Listening Test Dual Dichotic Listening Test (Trial 1) Dual Dichotic Listening Test (Trial 2) Dual Dichotic Listening Test (Trial 3) Single Axis Tracking (Stick-6 Minutes) Single Axis Tracking with Dual Dichotic Listening
SPSYXYZ DPSY2	(Trial 1) Stick and Rudder Tracking (Trial 1) Single Axis Tracking w/Dual Dichotic Listening (Trial 2)
DPSY3	Single Axis Tracking w/Dual Dichotic Listening (Trial 3)
M1XYZ	Three Axis Tracking, Stick and Rudder Scored (1st Minute)
MIXYT	Three Axis Tracking, Stick and Throttle Scored (1st Minute)
M1XYZT M2XYZ	Three Axis Tracking, All Axes Scored (1st Minute) Three Axis Tracking, Stick and Rudder Scored (2nd
M2XYT	Minute) Three Axis Tracking, Stick and Throttle Scored (2nd
M2XYZT	Minute) Three Axis Tracking, All Axes Scored (2nd Minute)

#### Prediction of Primary Setback and Attrition

In addition to grades, two other measures of performance are available; deficiency based attritions and setbacks. Attrition denotes individuals whose flight training is terminated due to reasons ranging from flight performance deficiency to medical emergency. Setback refers to individuals who are put into a following class, also for reasons ranging from flight deficiency to medical problems. Flight deficiency refers to a failure on the part of the student to progress in the performance of flight tasks to an acceptable degree. In the analyses performed here, only flight deficiency setbacks and attritions were considered. These performance measures were analyzed using Stepwise Multiple Discriminant Analyses. For all discriminant analyses, the value for F-to-enter was 1.00, F-to-remove was 0.996, and tolerance was set at 0.01.

#### Results

#### Prediction of Primary Grades

Table 3 presents a summary of the multiple regression analyses for prediction of primary grades. Sample sizes for these analyses range from 1783 to 2901 because subjects with missing data were excluded. The two individual grades for which sample sizes are smallest, EA06 (1783) and EF03 (2422), were reduced because the USAAVNC experimented with elimination of these performance evaluations during the time the research was Therefore, not all of the students who went through flight school during this period received those two grades. Note that the sample size for POAG (2901) exceeds that for any of the individual grades. Individual grades are reported by training units which also calculate the POAG. Frequently, one or more individual grades were missing for a particular student, yet the POAG was reported. In addition, the sample for the POAG analysis was taken several months after the samples for the other grades, and therefore, the available population was somewhat larger.

Residual analysis for these regressions did not reveal any threats to the assumptions of homogeneity, linearity, or homoscedasticity. However, in several cases, normalcy of the distribution of the dependent variable is questionable. academic grades EA01, EA02, EA03, EA05, EA06, EA07, EA08, EA12, and EA17 exhibit the effects of skewed distributions resulting from ceiling effects in the assignment of grades (e.g. a mean value of 97.6 out of a possible 100 with a standard deviation of 4.0 on variable EA06). This is not an uncommon occurrence in academic settings and may be indicative of grade "inflation" or of a well executed program of instruction. In addition, many of these grades are the culmination of a training to criterion approach in which the functional structure of the instructional unit is pass/fail, even though a numeric grade is assigned. For these grades, the skew in their distributions is expressed in the residuals analysis as apparent skew and/or leptokurtosis of the standardized residual distributions. The multiple regression

procraures are generally considered to be robust to these deviations from underlying assumptions.

Table 3

Summary Results of Multiple Regressions on Primary Grades
Using Test Battery Scores

Grade	N	Multiple R	R²	Adjusted R <sup>2</sup>
EF01	2781	0.2998	0.0899	0.0879
EF02	2781	0.2912	0.0848	0.0822
EF03*	2422	0.3867	0.1496	0.1471
EF04	2763	0.3353	0.1125	0.1099
POFG	2405	0.4358	0.1899	0.1869
EA01	2778	0.3414	0.1156	0.1137
EA02	2777	0.2763	0.0763	0.0740
EA03	2778	0.3569	0.1274	0.1249
EA04	2778	0.3223	0.1039	0.1016
EA05	2778	0.3063	0.0938	0.0912
EA06*	1783	0.3342	0.1117	0.1067
<b>EA</b> 07	2777	0.2369	0.0561	0.0527
EA08	2777	0.2926	0.0856	0.0833
EA09	2776	0.3270	0.1059	0.1046
EA10	2777	0.3550	0.1261	0.1232
EA12	2774	0.2514	0.0632	0.0598
EA17	2763	0.2124	0.0451	0.0427
EA23	2777	0.3236	0.1047	0.1011
POAG	2901	0.4496	0.2022	0.1991

<sup>\*</sup>These examinations were not given to all students.

The multiple Rs for individual flight grades ranged from 0.029 to 0.386, accounting for 8.4 to 14.7 percent of the variance. Multiple Rs for the individual academic grades ranged from 0.212 to 0.356 accounting for 4.2 to 12.4 percent of the variance. Multiple Rs of 0.435 and 0.447 were found for the POFG and POAG respectively, accounting for 18.6 and 19.0 percent of the variance. The probability that the observed magnitude of R' occurred by chance is less thin 0.0001 for all of these multiple regressions. These results definitely show the test battery can be used to predict student performance using grades as the criteria in every phase of primary flight training. A more detailed presentation of these analyses is found in Appendix A.

The tables in Appendix A contain unstandardized weights (B) and their standard errors, standardized weights (B) and their standard errors, the simple correlation of the predictor variable with the dependent variable  $(\underline{r})$ , and the squared semipartial correlation. They also show the sample size (N), the multiple correlation (R) of the vector of predictors with the dependent variable, the squared multiple correlation  $(R^2)$ , the squared multiple correlation adjusted for inflation  $(ADJR^2)$ , and the

probability that the observed magnitude of R<sup>2</sup> occurred by chance. The presence of suppressor variables (indicated by opposite signs of the simple correlation and B weight) in these analyses is common. In Table A6 variable DPSY3 is a suppressor. This variable also appears as a suppressor in Table A11. Table A18 contains three suppressors, DPSY2, M1XYZT and SPSYXYZ. Table A15 contains two suppressors, VULNER and COCKPIT. COCKPIT appears most frequently as a suppressor variable, also showing up in Tables A7, A12, A13, and A19.

#### Setback Prediction

Stepwise multiple discriminant analysis was used with setbacks and nonsetbacks as the two groups. Test Battery scores were used as the candidate predictor set. After separating the sample into Setbacks (302 students) and Nonsetbacks (2632 students) substantial differences in mean scores were observed between groups on most of the perceptual-motor skill subtests. Error scores were typically greater for the setback group than The differences in variance between groups, for nonsetbacks. however, do not appear to present a threat to validity of the underlying model from univariate heterogeneity of variance. largest ratio of variances between groups was 2.75:1 on variable The discriminant procedure terminated with a significant separation between groups [Wilk's Lambda = 0.9294 (accounting for 7 percent of the total variance), approximate F(11, 2922) =20.188, p < 0.0001], using 11 variables in the model. Inspection of the distributions for the two groups did not reveal any obvious differences in magnitude or shape of dispersions.

The classification rates for this analysis are presented in Table 4. When a classification procedure is performed on the same cases used to develop the classification functions, a bias may result in the outcome. As a consequence, estimates of the success rate for classifications of a new set of cases may be inflated. This bias is substantially reduced by performing a jackknifed classification procedure. In the jackknifed procedure each case is classified according to a set of equations developed with that case excluded. Therefore, the jackknifed procedure provides a more conservative estimate of the ability of the predictor variables to correctly discriminate group membership for novel cases. Results from both direct and jackknifed classification procedures are reported. Students were correctly classified at much better than the 50 percent chance rate. standardized canonical function coefficients and the classification function coefficients for this analysis are shown in Tables 5 and 6.

Although no clear threats to univariate or multivariate homogeneity of variance are evident, the large difference in sample size between groups entails high sensitivity to departures from the homogeneity assumption, and requires that caution be used in interpreting the results of this analysis. Discriminant analysis with prior probabilities set to match group membership probabilities observed in the sample (.89 for Nonsetbacks and .11

for Setbacks) resulted in an improved total correct classification rate (89 percent), but identification of Setbacks was far below the chance rate. Setbacks were correctly classified in only 6.5 percent of the cases.

Table 4
Classification Capability of Test Battery for Setback Versus Non-Setback Students in Primary Training

#### <u>Direct Classification</u>

	Percent Correct	Number of Cases Classified Into Grou		
Group	<u>Classification</u>	<u>NSTBK</u>	<u>STBK</u>	
NonSetbacks	72.2	1900	732	
Setbacks	65.2	105	197	
Total	71.5	2005	929	

#### Jackknife Classification

	Percent	Number <u>Cases Classifie</u>	
Group	Correct <u>Classification</u>	<u>NSTBK</u>	STBK
NonSetbacks	72.0	1894	738
Setbacks	62.9	112	190
Total	71.0	2006	928

Table 5
Standardized Canonical Discriminant Function Coefficients for Primary Training Setbacks

<u>Variable</u>	<u>Coefficient</u>	
VULNER	-0.09277	
CLUSTER4	-0.10725	
MARKNUM	0.39906	
NUMWORDS	0.13212	
MANIKIN	0.14198	
DDLT1	0.25369	
SPSY6	-0.34241	
SDSY1	0.21218	
DPSY2	-0.51693	
DPSY3	0.18370	
M1XYT	-0.25220	
(CONSTANT)	-4.03268	

Table 6
Classification Function Coefficients for Primary Training Setbacks

<u>Variable</u>	<u>Nonsetbacks</u>	<u>Setbacks</u>
VULNER	4.85093	4.98502
CLUSTER4	-0.34203	-0.32544
MARKNUM	0.02479	0.02279
NUMWORDS	0.03269	0.03189
MANIKIN	0.43309	0.40973
DDLT1	0.35519	0.32096
SPSY6	0.00007	0.00010
SDSY1	-0.00019	-0.00023
DPSY2	0.00036	0.00043
DPSY3	0.00018	0.00016
M1XYT	0.00025	0.00027
(CONSTANT)	-64.17175	-60.84102

#### Attrition Prediction

Stepwise multiple discriminant analysis was used with attrites and nonattrites as the two groups. Test Battery scores were used as the candidate predictor set. After separating the sample into Attrites (50 students) and Nonattrites (2884 students) no gross differences in mean scores were observed between groups. There were also no notably large differences in variance between groups. The largest ratio of variances between groups was 1.94:1 on variable M1XYZ. The discriminant procedure terminated with a significant separation between groups [Wilk's Lambda = 0.9813, approximate F(13, 2920) = 4.288, p < 0.0001], using 13 variables in the model. This model accounts for less than 2 percent of the total variance. The classification rates for this analysis are presented in Table 7. Students were correctly classified at only slightly better than the 50 percent chance rate. The standardized canonical function coefficients and the classification function coefficients for this analysis are shown in Tables 8 and 9.

Although no clear threats to univariate or multivariate homogeneity of variance are evident, the large difference in sample size between groups entails high sensitivity to departures from the homogeneity assumption, and requires that caution be used in interpreting the results of this analysis.

Table 7

Classification Capability of Test Battery for Attrite Versus Non-Attrite Students in Primary Training

#### <u>Direct Classification</u>

	Percent	Number of Cases Classified Into Gre	
Group	Correct <u>Classification</u>	NATTR	<u>ATTR</u>
Nonattrites	74.8	2156	728
Attrites	66.0	17	33
Total	74.6	2173	761

#### Jackknife Classification

	Percent Correct	Number Cases Classified	
Group	<u>Classification</u>	<u>NATTR</u>	<u>ATTR</u>
Nonattrites	74.5	2148	736
Attrites	54.0	23	27
Total	74.1	2171	763

Table 8

Standardized Canonical Discriminant Function Coefficients for Primary Training Attritions

<u>Variable</u>	Coefficient				
COMP1 5	0.50202				
COMP15	0.50393				
COCKPIT	-0.39832				
LEADER	-0.23550				
VULNER	-0.17009				
CLUSTER5	0.31586				
TOWER	0.20105				
INFOPUR	0.40564				
SDLT	0.40564				
DDLT1	-0.33712				
SPSY6	0.22962				
SPSYXYZ	-0.40358				
M2XYT	1.23933				
M2XYZT	-1.64300				
(CONSTANT)	-13.71503				

Table 9
Classification Function Coefficients for Primary Training Attritions

<u>Variable</u>	<u>Nonattrites</u>	<u>Attrites</u>
COMP15	185.09850	184.40650
COCKPIT	-59.28346	-58.53899
LEADER	1.19462	1.94635
VULNER	-15.36804	-15.07877
CLUSTER5	0.09141	0.06339
TOWER	0.00743	0.00677
INFOPUR	0.08712	0.08551
SDLT	0.43242	0.41509
DDLT1	-0.18787	-0.16581
SPSY6	0.00003	0.00001
SPSYXYZ	0.00010	0.00011
M2XYT	-0.00040	-0.00053
M2XYZT	0.00037	0.00052
(CONSTANT)	<del>-</del> 931.58080	-917.49540
<del> </del>		

#### Discussion and Conclusion

The analyses reported here are based on large samples which approximate the total population available at the time the research was carried out. Academic grades present a typical picture of ceiling effect, possibly because of the presence of a training to criterion approach combined with assessment instruments designed for non dichotomous performance measurement. Inspection of the tables in Appendix A reveals prediction of flight grades is heavily dependent on the subscores of the Complex Coordinated Multi-Tasking Battery (CCMB) test while the prediction of academic grades is more dependent on the Complex Cognitive Abilities Battery (CCAB) subscores. The Primary Overall Average Grade (POAG), of course, includes equal contributions from all the other grades. Prediction of individual primary flight and academic grades is shown to be successful using the Multi-Track Test Battery subscores. Prediction of composite grades is, not unexpectedly, better than prediction of the individual grades that constitute them.

Flight deficiency setback and flight deficiency attrition are not as well quantified. The large differences between sample sizes for groups presents a possible threat to validity of the discriminant analyses. Other indications of departures from underlying assumptions are minimal. Although the overall analyses are statistically significant their practical utility (where only 7 percent or 2 percent of the total variance is accounted for) is not certain. The discriminant analyses should be viewed only as one indicator among many and should require confirmation (as with low academic grades on entry) before identifying an at-risk student.

These results provide evidence that the Multi-Track Test Battery can be used to predict flight student performance at a very early stage and provides a useful management tool for identification of students with low probability of successfully completing flight training.

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#### APPENDIX

Regression Analysis Summary of Test Battery Predicting Primary Grades

Regression Analysis Summary of Test Battery Predicting Primary Grade, EF01

VARIABLE	<u>B</u>		Std Err	<u>B</u>	Std Err	ŗ	<u>Semipartial r<sup>2</sup></u>
DPSY3	-3.422	91E-05	1.61071E-05	08010	.03769	2581	.0015
M1XYZT	-3.038	11E-05	7.95864E-06	09494	.02487	2463	.0048
DDLT2	0.011	60	3.19457E-03	.07005	.01929	.1590	.0043
SPSY6	-1.475	60E-05	5.20680E-06	06075	.02144	1944	.0026
CLUSTER5	0.013	65	5.11779E-03	.04845	.01816	.0652	.0023
DPSY3	-3.727	73E-05	1.1639E-05	07754	.03669	2543	.0015
(CONSTANT) 86.98178		78	0.55467				
<u>N</u>	<u>R</u>	<u>R²</u>	ADJR2	<u>P</u>			
2781	. 2998	.0899	.0879	< 0.0001			

Regression Analysis Summary of Test Battery Predicting Primary Grade, EF02

VARIABLE	<u>B</u>		Std Err	<u>B</u>	Std Err	<u>r</u>	Semipartial r <sup>2</sup>
M1XYZT	-3.403	42E-05	8.52373E-06	09940	.02489	2310	.0053
DPSY3	-4.889	51E-05	1.11819E-05	10694	.02446	2285	.0063
MARKNUM	1.493	96E - 03	3.83612E-04	.07562	.01942	. 1433	.0050
DDLT2	0.020	25	5.79523E-03	.11430	.03270	.1564	.0040
SPSY6	-1.448	99E-05	5.58206E-06	05575	.02148	1788	.0022
MANIKIN	0.032	02	0.01266	.04890	.01934	. 1285	.0021
DDLT3	-0.013	42	6.26965E-03	06983	.03262	.1244*	.0015
VULNER	-0.219	14	0.10532	03789	.01821	0294	.0014
(CONSTANT) 86.25760		0.65300					
N		6.7	AD 107				
<u>N</u>	<u>R</u>	<u>R²</u>	ADJR <sup>2</sup>	<u>P</u>			
2781	.2912	.0848	.0822	< 0.0001			

<sup>\*</sup>The correlation of DDLT3 with EF02 and its B weight have opposite signs, indicating that DDLT3 operates as a suppressor variable in this model.

Regression Analysis Summary of Test Battery Predicting Primary Grade, EF03

VARIABL	<u>.E</u>	<u>B</u>	Std Err	<u>B</u>	Std Err	Ţ	<u>Semipartial r<sup>2</sup></u>
DPSY2	-9.61	749E-05	1.24227E-05	18437	.02381	3192	.0211
MARKNUM	2.27	884E-05	4.01287E-04	.11455	.02017	.2119	.0114
MZXYZT	-3.34	745E-05	8.40521E-06	09439	.02370	2756	.0056
SPSY6	-2.22	693E-05	5.75071E-06	08524	.02201	2378	.0053
NUMWORE	s 1.75	974E-03	4.80994E-04	.07259	.01984	. 1595	.0047
SDLT	7.46	073E-03	2.73802E-03	.05199	.01908	.1155	.0026
CLUSTER	1 0.01	210	5.37358E-03	.04237	.01881	.0604	.0018
(CONSTANT) 82.90762			1.09107				
N	<u>R</u>	<u>R²</u>	AD JR 2	<u>P</u>			
2422	.3867	. 1496	. 1471	< 0.0001			

Regression Analysis Summary of Test Battery Predicting Primary Grade, EF04

VARIABLE	<u>B</u>		Std Err	<u>B</u>	Std Err	r	Semipartial r <sup>2</sup>
MARKNUM	3.46920E	-03 (	6.24131E-04	. 12361	.02224	.2348	.0100
DPSY2	-7.25793E	-05	1.67700E-05	09914	.02291	2297	.0060
M2XYZT	-3.83561E	-05	1.15924E-05	07555	.02283	2125	.0035
WORDANA	2.36465E	-03	7.84844E-04	.06733	.02235	.2099	.0029
NUMWORDS	1.92194E	-03 (	6.65247E-04	.05592	.01935	.1568	.0027
SPSY6	-2.27017E	-05	7.79176E-06	06152	.02111	1761	.0027
MANIKIN	0.04644	1	0.01813	.04973	.01941	. 1637	.0021
CLUSTER1	0.01829	•	7.30213E-03	.04504	.01798	.0604	.0020
(CONSTANT)	75.39238		1.37463				
	•	6.7	40.107	•			
N	<u>R</u>	<u>R²</u>	ADJR <sup>2</sup>	<u>P</u>			
2763	.3353	.1125	. 1099	< 0.0001			

#### Regression Analysis Summary of Test Battery Predicting Primary Overall Flight Grade, POFG

VARIABLE		1	Std Err	<u>8</u>	Std Err	ī	Semipartial r <sup>2</sup>
DPSY2	-6.790	)57E-05	1.03883E-05	15939	.02438	3427	.0145
MARKNUM	2.149	73E - 03	3.29500E-04	. 13262	.02033	.2518	.0144
M2XYZT	-2.172	21 <b>3</b> E - 05	8.38607E-06	07500	.02896	3110	.0023
NUMWORDS	1.457	743E-03	3.88501E-04	.07367	.01964	. 1829	.0048
SPSY6	-1.722	212E - 05	4.67407E-06	08094	.02197	2618	.0046
DDLT2	7.805	01E-03	2.85706E-03	.05500	.02013	.2156	.0025
CLUSTER1	0.01	147	4.29494E-03	.04921	.01843	.0666	.0024
MANIKIN	0.026	669	0.01063	.04950	.01972	.1888	.0021
MIXYZ	-2.636	662E - 05	1.27988E-05	06246	.03032	3113	.0014
(CONSTAN	IT) 82.076	35	0.81471				
ñ	<u>R</u>	<u>R'</u>	ADJR <sup>2</sup>	<u>P</u>			
2405	.4358	. 1899	. 1869	< 0.0001			

Regression Analysis Summary of Test Battery Predicting Primary Grade, EA02

VARIABLE	<u> </u>	<u> </u>	Std Err	<u>B</u>	Std Err	Ţ	Semipartial r <sup>2</sup>
WORDKNOW	5.261	126	0.84221	.12040	.01927	.1789	.0130
MARKNUM	2.838	310E-03	5.03431E-04	.11006	.01952	. 1744	.0106
MANIKIN	0.072	269	0.01655	.08532	.01943	. 1540	.0064
COMP15	1.969	91	0.38700	.13387	.02630	. 1095	.0086
SPSYXYZ	-1.21003E-05		3.32103E-06	06844	.01878	1033	.0044
CLUSTER3	-0.035	593	0.01308	05027	.01831	0423	.0025
COCKPIT	-0.511	144	0.21452	06223	.02610	.0228*	.0019
(CONSTANT) 70.28929		3.53383					
	_			_			
Ñ	Ŗ	<u>R²</u>	ADJR <sup>2</sup>	<u>P</u>			
2777	. 2763	.0763	.0740	< 0.0001			

<sup>\*</sup>The correlation of COCKPIT with EAO2 and its B weight have opposite signs, indicating that COCKPIT operates as a suppressor variable in this model.

#### Regression Analysis Summary of Test Battery Predicting Primary Grade, EA04

VARIABLE	<u>B</u>		Std Err	<u>B</u>	Std Err	Ţ	Semipartial r <sup>2</sup>
WORDKNOW	11.82279		1.32838	.16749	.01882	.2239	.0256
MARKNUM	5.58064	E-03	8.03175E-04	. 13448	.01935	.2152	.0156
M1XYZT	-6.49812	E-05	1.37531E-05	09037	.01913	1413	.0072
MANIKIN	0.09979		0.02642	.07253	.01920	.1637	.0046
COMP15	1.59291		0.43194	.06702	.01817	.0945	.0044
CLUSTER4	-0.06338		0.02349	04874	.01806	0279	.0024
DDLT1	0.02061		9.01557E-03	.04335	.01896	.1180	.0017
(CONSTANT)	55.08961		4.66576				
M		n?	AD 102				
<u>N</u>	Ŗ	<u>R²</u>	ADJR <sup>2</sup>	<u>P</u>			
2778	.3223	.1039	.1016	< 0.0001			

Regression Analysis Summary of Test Battery Predicting Primary Grade, EA05

VARIABLE	<u>B</u>		Std Err	<u>B</u>	Std Err	ŗ	Semipartial r <sup>2</sup>	
MARKNUM	5.8893	34E-03	8.19994E-04	.14467	.02014	.2209	.0169	
MANIKIN	0.1322	29	0.02620	.09803	.01942	.1819	.0083	
M1XYZ	-1.0257	72E - 04	1.97549E-05	09647	.01858	1421	.0088	
WORDKNOW	6.1802	27	1.30864	.08926	.01890	.1512	.0073	
COMP15	2.0072	26	0.44281	.08609	.01899	.0877	.0067	
VULNER	-0.6464	<b>5</b>	0.22507	05425	.01889	0075	.0027	
CLUSTER4	-0.0662	21	0.02320	05191	.01819	0265	.0027	
TOWER	1.2293	32E-03	4.43430E-04	.05392	.01945	. 1388	.0025	
(CONSTANT) 56.26309		4.61829						
<u>N</u>	<u>R</u>	R2	ADJR2	P				
2	<u>=</u>	~	<u> HOUR</u>	<u>.</u>				
2778	.3063	.0938	.0912	< 0.0001				

Regression Analysis Summary of Test Battery Predicting Primary Grade, EA06

VARIABLE	<u>B</u>		Std Err	<u>B</u>	Std Err	<u>r</u>	Semipartial r <sup>2</sup>
MARKNUM	2.6589	3E-03	5.13027E-04	.12506	.02413	.1816	.0135
M1XYT	-5.4939	6E-05	1.84691E-05	12555	.04221	1511	.0044
SPSYXYZ	3.5327	2E-05	4.96703E-06	.25291	.03556	.0321	.0254
COMP25	1.6767	75	0.33552	.11228	.02247	.1221	.0125
DDLT1	0.0220	14	5.82014E-03	.09050	.02390	.1303	.0072
M2XYT	-6.5281	2E-05	1.95176E-05	13980	.04180	1517	.0056
SPSY6	-2.1886	8E-05	7.96107E-06	07958	.02894	0720	.0038
MANIKIN	0.0435	9	0.01705	.06128	.02396	.1220	.0033
INFOPUR	1.8523	SE-03	8.59033E-04	.04836	.02243	.0551	.0023
DPSY3	3.4969	71E-05	1.63147E-05	.07019	.03275	0091*	.0023
(CONSTANT	83.2501	7	1.64370				
<u>N</u>	<u>R</u>	<u>R²</u>	ADJR <sup>2</sup>	<u>P</u>			
1783	.3342	.1117	.1067	< 0.0001			

<sup>\*</sup>The correlation of DPSY3 with EAO6 and its B weight have opposite signs, indicating that DPSY3 operates as a suppressor variable in this model.

Regression Analysis Summary of Test Battery Predicting Primary Grade, EA07

VARIABLE	<u>B</u>		Std Err	<u>B</u>	Std Err	<u>r</u>	Semipartial r <sup>2</sup>
SPSYXYZ	-2.0776	4E-05	3.93364E-06	10408	.01971	1422	.0095
MARKNUM	1.6311	2E-03	6.04616E-04	.05623	.02084	. 1233	.0025
MANIKIN	0.0606	7	0.01916	.06310	.01993	.1273	.0034
CLUSTER3	-0.0494	0	0.01513	06121	.01875	0644	.0036
COMP15	1.7090	1	0.44217	.10287	.02662	.0693	.0051
COCKPIT	-0.5071	9	0.24640	05466	.02652	.0029*	.0015
CLUSTER4	-0.0438	7	0.01714	04827	.01886	0448	.0022
TOWER	7.4653	0E-04	3.23675E-04	.04590	.01990	.1009	.0018
WORDKNOW	2.2555	0	0.96155	.04571	.01949	.0905	.0019
DDLT2	0.0108		5.18464E-03	.04154	.01993	.1090	.0015
(CONSTANT	75.0372	9	4.05987				
<u>N</u>	<u>R</u>	<u>R²</u>	ADJR2	<u>P</u>			
2777	. 2369	.0561	.0527	< 0.0001			

<sup>\*</sup>The correlation of COCKPIT with EA07 and its 8 weight have opposite signs, indicating that COCKPIT operates as a suppressor variable in this model.

#### Regression Analysis Summary of Test Battery Predicting Primary Grade, EA08

VARIABLE	<u>B</u>		Std Err	<u>B</u>	Std Err	Ţ	Semipartial r <sup>2</sup>
MARKNUM	4.761	107E-03	6.25578E-04	. 14916	.01960	.2204	.0191
WORDKNOW	6.476	573	1.03910	.11930	.01914	. 1853	.0128
MANIKIN	0.088	300	1.34922E-05	.08314	.01940	.1657	.0061
M2XYT	-3.220	017E-05	1.34922E-05	04633	.01941	1085	.0019
COMP15	1.702	290	0.47861	.09311	.02617	.0770	.0042
DDLT3	0.013	312	6.01216E-03	.04224	.01936	.1126	.0016
COCKPIT	-0.558	356	0.26526	05468	.02597	.0014*	.0015
(CONSTANT	ANT) 64.26102		4.30771				
	_			_			
Ň	<u>R</u>	<u>R²</u>	ADJR?	<u>P</u>			
2777	.2926	.0856	.0833	< 0.0001			

<sup>\*</sup>The correlation of COCKPIT with EAO8 and its 8 weight have opposite signs, indicating that COCKPIT operates as a suppressor variable in this model.

Regression Analysis Summary of Test Battery Predicting Primary Grade, EA09

VARIABLE	<u> 8</u>	<u>1</u>	Std Err	<u>B</u>	Std Err	Ţ	Semipartial r <sup>2</sup>
MARKNUM	5.566	58E-03	6.83044E-04	.15790	.01937	.2383	.0214
MANIKIN	0.135	50	0.02238	.11591	.01914	.2018	.0118
WORDKNOW	7.080	068	1.12543	.11804	.01876	. 1911	.0128
COMP15	1.469	45	0.36615	.07275	.01813	.0942	.0052
M2XYT	-4.551	21E-05	1.45114E-05	05928	.01890	1297	.0032
DDLT1	0.023	35	7.57545E-03	.05779	.01875	. 1303	.0031
CLUSTER	STER3 -0.04081		0.01767	04157	.01800	0304	.0017
(CONSTANT) 61.55721			3.99898				
N	<u>R</u>	R²	ADJR2	<u>P</u>			
N	7	<u>K</u>	WORK.	<u>r</u>			
2776	.3270	.1059	.1046	< 0.0001			

Regression Analysis Summary of Test Battery Predicting Primary Grade, EA10

VARIABLE	<u>B</u>		Std Err	<u>B</u>	Std Err	ŗ	Semipartial r <sup>2</sup>
MARKNUM	5.360	02E-03	5.87360E-04	.17383	.01905	.2521	.0263
WORDKNOW	7.729	81	0.98325	.14739	.01875	.2255	.0195
MANIKIN	0.115	08	0.01938	.11256	.01896	.2050	.0111
COMP15	1.488	38	0.75887	.08425	.04296	.1095	.0012
M1XYZT	-3.468	74E-05	9.81103E-06	06493	.01836	1227	.0039
COCKPIT	-0.940	63	0.25783	09533	.02613	.0093*	.0042
VULNER	-0.716	73	0.21956	07941	.02433	.0163*	.0034
CLUSTER	-0.032	76	0.01534	03819	.01789	0218	.0014
COMP25	2.154	50	1.03089	.09959	.04765	.1011	.0014
(CONSTANT) 61.96312		5.25470					
Ň	<u>R</u>	<u>R²</u>	ADJR2	<u>P</u>			
2777	.3550	. 1261	.1232	< 0.0001			

<sup>\*</sup>The correlations of COCKPIT and VULNER with EA10 weight have opposite signs from their 8 weights, indicating that COCKPIT and VULNER operate as a suppressor variables in this model.

Regression Analysis Summary of Test Battery Predicting Primary Grade, EA12

VARIABL	<u>.E</u>	<u>B</u>	Std Err	<u>B</u>	<u>Std Err</u>	ŗ	Semipartial r <sup>2</sup>
WORDKNO	NH 4.45	163	0.92855	.09324	.01945	. 1493	.0078
MARKNUM	2.54	908E - 03	5.59760E-04	.09084	.01995	.1318	.0070
COMP15	1.92	610	0.42671	.11971	.02652	.0936	.0069
DPSY2	5.57	522E-05	1.92009E-05	.07610	.02621	.0399	.0029
MANIKIN	0.06	645	0.01838	.07138	.01975	.1095	.0044
DDLT1	0.02	148	6.28368E-03	.06677	.01953	.0810	.0040
CLUSTER	4 -0.04	859	0.01633	05524	.01857	0468	.0030
M2XYT	-5.56	975E-05	1.44632E-05	09112	.02366	0444	.0050
SPSYXYZ	1.77	182E-05	5.33384E-06	.09149	.02754	.0436	.0037
COCKPIT	-0.50	035	0.23756	05568	.02644	.0141*	.0015
(CONSTANT) 65.56803			3.86562				
Ň	<u>R</u>	<u>R²</u>	ADJR2	<u>P</u>			
2774	.2514	.0632	.0598	< 0.0001			

<sup>\*</sup>The correlation of COCKPIT with EA12 and its B weight have opposite signs, indicating that COCKPIT operates as a suppressor variable in this model.

Regression Analysis Summary of Test Battery Predicting Primary Grade, EA17

VARIABLE	<u>B</u>		Std Err	<u>B</u>	Std Err	ī	Semipartial r <sup>2</sup>
WORDKNOW	8.89646		1.29482	. 13308	.01937	.1628	.0164
MARKNUM	2.35558	E-03	7.88157E-04	.05995	.02006	.1229	.0031
SPSYXYZ	-1.12324	E-05	5.42653E-06	04149	.02004	0766	.0015
MANIKIN	0.06143		0.02596	.04699	.01986	.1046	.0019
CLUSTER5	0.02930		0.01158	.04883	.01930	.0539	.0022
VULNER	0.46930		0.22208	.04077	.01929	.0463	.0015
DDLT3	0.01531		7.66697E-03	.04002	.02003	.0872	-0014
(CONSTAN	78.50183		1.67274				
M		0.2	AD 102				
N	<u>R</u>	<u>R?</u>	ADJR?	<u>P</u>			
2763	.2124	.0451	.0427	< 0.0001			

Regression Analysis Summary of Test Battery Predicting Primary Grade, EA23

VARIABLE	<u>B</u>		Std Err	<u>B</u>	Std Err	Ţ	Semipartial r <sup>2</sup>
MARKNUM	6.85582	E-03	7.82772E-04	.17075	.01950	.2343	.0248
MANIKIN	0.11437		0.02572	.08590	.01932	.0193	.0064
M1XYT	-2.17258	E-04	4.84349E-05	26070	.05812	1463	.0065
WORDKNOW	5.20880		1.30004	.07627	.01904	. 1481	.0052
COMP15	2.52655		0.59673	.10983	.02594	.0914	.0058
DPSY2	6.80183E-05		2.71154E-05	.06508	.02594	0568	.0020
DDLT1	0.03004		8.83194E-03	.06528	.01920	. 1274	.0037
M1XYZT	1.05986E-04		4.30912E-05	. 15326	.06195	1199	.0020
SPSY6	-4.15521	E-05	1.20708E-05	07868	.02286	1101	.0038
COCKPIT	-0.69312		0.33106	05395	.02577	.0116	.0014
SPSYXYZ	1.72850E-05		8.32065E.06	.06257	.03012	0591	.0014
(CONSTANT)	45.4 <b>99</b> 10		5.40903				
N	<u>R</u>	<u>R²</u>	ADJR2	<u>P</u>			
2777	.3236	. 1047	.1011	< 0.0001			

<sup>\*</sup>The correlations of DPSY2, M1XYZT and SPSYXYZ with EA23 have opposite signs from their B weights, indicating that these operate as suppressor variables in this model.

Regression Analysis Summary of Test Battery Predicting Primary Overall Average Grade, POAG

VARIABLE	<u>B</u>		Std Err	<u>B</u>	Std Err	Ţ	<u>Semipartial r<sup>2</sup></u>
MARKNUM	3.11226	E-03	2.96477E-04	.01847	.01847	.3129	.0304
M1XYZT	-2.779331	E-05	6.41356E-06	09987	.02305	2793	.0052
MANIKIN	0.05040		9.58543E-03	.09430	.01793	.2385	.0076
WORDKNOW	2.28198		0.48444	.08286	.01759	.1731	.0061
DPSY3	-3.44351	E-05	8.34026E-06	09276	.02247	2699	.0047
COMP15	1.05884		4.20647E-06	.11389	.02395	.1027	.0062
SPSY6	-1.65732	E-05	2.60042E-03	07783	.01975	.2228	.0043
DDLT2	8.37420	E-03	3.90105E-03	.05815	.01806	.2109	.0029
CLUSTER1	9.61695	E-03	3.52939E-04	.04119	.01671	.0708	.0017
NUMWORDS	9.11844	E-04	0.12284	.04608	.01784	. 1847	.0018
COCKPIT	-0.25148		0.12284	04855	.02372	.0204*	.0012
(CONSTANT)	70.05201		2.06319				
Ñ	<u>R</u>	<u>R²</u>	ADJR2	<u>P</u>			
2901	.4496	.2022	.1991	< 0.0001			

<sup>\*</sup>The correlation of COCKPIT with POAG and its B weight have opposite signs, indicating that COCKPIT operates as a suppressor variable in this model.